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The Role of Target Pre-acquisition Relationships on Acquisition Likelihood and Invention Outcomes

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The Role of Target Pre-acquisition Relationships on Acquisition Likelihood and Invention Outcomes

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I am the author of this thesis, and the work described therein was carried out by myself personally.

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Huma Javaid
Doctor of Philosophy

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Abstract

This thesis explores the role of inter-organisational relationships of firms, namely, corporate venture capital investments and alliances, in acquisitions and innovation performance. Drawing on signalling theory and a unique dataset of acquisitions of UK high technology firms, this work addresses three questions: (1) What is the influence of inter-organisational relationships of firms on the likelihood of being acquired? (2) What is the effect of inter-organisational relationships of firms on the post-acquisition innovation performance of acquired firms? and (3) What is the impact of selecting an acquisition target on the basis of the existence of inter-organisational relationships on the innovation performance of the merged (acquiring and acquired) firms?

The thesis comprises of three studies. The first study examines the relationship between inter-organisational partnerships and acquisitions and identifies the boundary conditions that affect target firm selection. To predict choice of target firm, each acquired firm is paired with non-acquired firms using coarsened exact matching method and then a logit model is applied on the matched dataset. A longitudinal investigation of 2,302 acquired and non-acquired firms in the high technology sector of the U.K., during the period 2008 – 2016, reveals a significantly positive relationship between the two types of inter-organisational relationships examined and the acquisition likelihood. Further, as predicted, this relationship is stronger for start-up firms. However, contrary to my expectations, affiliation with high reputation partners weaken the effect of inter-organisational relationships on the acquisition likelihood. Taken together, these findings are consistent with the view that inter-organisational relationships are perceived by acquirers as signals of firm quality when seeking acquisition targets – particularly when their information disadvantage is greater.

The second study explores the signalling value of the inter-organisational relationships of acquired firms after an acquisition. This study combines the matching methodology with a difference-in-difference-in-differences approach to observe the effect of an acquisition on innovation performance as a function of inter-organisational relationships of the targets. The results on a sample of 3,424 acquired and non-acquired high technology firms show a positive impact of inter-organisational relationships of acquired firms on their post-acquisition innovation performance as compared to acquired firms without inter-organisational relationships. Further, the third study evaluates the effect of target inter-organisational relationships on the combined (acquired and acquiring firms) innovation performance using a sample of 1,303 merged and non-merged pairs. The results indicate a decline in post-acquisition innovation performance of merged firms, whose targets are engaged in inter-firm ties, relative to their counterparts.

This research contributes to the understanding of the signalling effect of inter-organisational relationships that can provide an information advantage in the M&A market and brings forward the challenges faced by acquirers in acquiring and redeploying inter-organisational relationships, while managing the combined innovation activity.

CHAPTER 1

1.1 Introduction

The selection of an appropriate acquisition target has been acknowledged as an important determinant of the value creation potential of a deal by both strategy research and management practice (Graebner et al., 2010; King et al., 2004, Haleblian et al., 2009). Most acquirers carry out extensive due diligence on promising acquisition target firms in order to collect as much information as possible and decide whether a particular deal can further their strategic objectives. No matter how thorough the due diligence process is, acquirers have some information disadvantage regarding the actual nature and value of a target firm's assets relative to this target's managers. Prior research has shown that the acquirers' information disadvantage is greater when they acquire privately held firms (Capron and Shen, 2007, Fuller et al., 2002). In some rather extreme cases, target firm managers may even misrepresent the actual nature or value of their companies' assets. For example, the former Autonomy CEO, Mike Lynch, has been convicted by the US Department of Justice for misrepresenting Autonomy's finances in the lead up to the company's $11 billion sale to HP in 2011 (Fortune, 2018).

Acquiring firm managers rely on a wide spectrum of information in an attempt to overcome their information disadvantage and assess the underlying target firm quality more objectively. Their pre-acquisition audit usually extends well beyond the financial and legal position of a promising target firm and includes its production systems, intellectual property, organisational structure, processes and culture, as well as information systems (Harvey and Lusch, 1995; Chakrabarti and Mitchell, 2016). However, it is becoming increasingly recognized that inter-organisational relationships, such as corporate venture capital investments and alliances, may also need to be considered when evaluating firms (Nicholson et al., 2005; Reuer et al., 2012). Such relationships may reveal additional and valuable information about the underlying quality of promising acquisition targets.

The M&A literature has only recently started to examine systematically the role of inter-organisational relationships of firms through different theoretical perspectives to understand target selection mechanism and the associated performance outcomes (Mazzola et al., 2016; Meschi et al., 2017; Zaheer et al., 2010). In this regard, this research takes a signalling perspective to explain acquirer's search for acquisition opportunities and the boundary conditions that influence acquirer's choice of target. There also exists an opportunity in the literature to investigate the value of signals and whether firms with inter-organisational relationships outperform firms that lack such relationships after an acquisition. In my research, I seek to address the following questions: (1) What is the influence of inter-organisational relationships of firms on the likelihood of being acquired? (2) What is the effect of inter-organisational relationships of firms on the post-acquisition innovation performance of acquired firms? and (3) What is the impact of selecting an acquisition target on the basis of the existence of inter-organisational relationships on the innovation performance of the merged (acquiring and acquired) firms?

Specifically, I focus on the high technology sector in the UK. Based on Akerlof's (1970) market for lemons, sellers possess superior information about the quality of their products than the buyers. This makes it difficult for acquiring firms to evaluate the true quality of potential target firms and leads to the risk of adverse selection. According to signalling mechanism, information about quality of products is transmitted in the form of signals through characteristics that are costly and difficult to imitate (Spence, 1973). The signals enable acquirers to distinguish between high quality firms and low quality firms, thus mitigating the risk of information asymmetry and adverse selection.

Building on signalling theory, I argue that the inter-organisational relationships increase takeover likelihood as they enhance "visibility" and provide "endorsement" of firm quality (Mazzola et al., 2016; Stuart et al., 1999). Inter-organisational relationships are costly to build and difficult to imitate, allowing firms to “stand-out from the crowd” (Pollock and Gulati, 2007). This relationship is moderated under the condition of a firm being a start-up. The difficulty associated with assessing quality of young start-up firms tends to be lower for firms engaged in inter-organisational relationships (Baum and Silverman, 2004). In addition, I predict that high reputation ties symbolize and endorse a firm’s strength (Pollock et al., 2009) which affects perceptions of acquirers about quality of firms and increases acquisition likelihood.

Firms engaged in inter-organisational relationships provide valuable information to acquirers to alleviate information asymmetry and adverse selection problems and increase technological innovation through their operating synergies (Stuart et al., 1999; Stuart, 2000; Graebner et al., 2010). The signalling value of the acquired firm’s connections leads to an increase in innovation performance post-acquisition. The enhanced information available through target relationships can help the acquirer better design and implement the target integration process and increase combined post-deal performance.

The next section provides an overview of the studies comprising my dissertation essay. The essay outlines the research design, analytical methods and how I aim to contribute to the wider academic research and intellectual debate on the subject.

1.2 Overview of the Dissertation Essay

To investigate the questions outlined above, I conducted three empirical studies. The first study analyses the influence of inter-organisational relationships of firms on the probability of being acquired and identifies the boundary conditions under which such a phenomenon is most likely to hold stronger. In my research, inter-organisational relationships are defined as corporate venture capital (CVC) investments and alliances[1]. It can be expected

[1] CVC investments are defined as minor equity investments pursued by established corporations that extend their corporate venture capital arm to invest in entrepreneurial firms seeking capital for growing its operations (Dushnitsky, 2012; Gompers and Lerner, 1998). Alliances are defined as voluntary cooperative agreement in

that a firm's likelihood of being acquired will increase as CVC investments and alliances provide enhanced information, overcome adverse selection risk and signal quality of firms. The likelihood of being acquired will be strengthened under boundary conditions examining the moderating effect of being a start-up and the reputation of CVC investors and alliance partners connected to a focal firm. The theory and hypotheses development of this study are described in Chapter 3[2].

The second study is motivated by the findings of the first study which depicts direct effects of inter-organisational relationships on the likelihood of being acquired. The core research question is then whether an acquisition will induce a more favourable environment for innovation in a target firm. In doing so, the research sheds light on the effect of an acquisition on innovation outcomes by focusing on the characteristics of acquired firms in terms of the information conveyed by their inter-organisational relationships. One would expect that acquired firms will increase innovation output because acquired firms benefit from the operating synergies of their inter-organisational relationships. Chapter 4 provides a thorough discussion on the theory and hypotheses development of this study. Following on from these two studies, the third study examines the impact of inter-organisational relationships of target firms on the post-acquisition innovation output of the merged (acquiring and acquired) firms. The combined entities can be expected to increase innovation output as acquirers can benefit from the enhanced information provided by the inter-organisational relationships of acquired firms to manage the acquisition process. On the other hand, it can take considerable amount of time and deliberate effort to materialize gains post-acquisition as it can be difficult to manage a large network of partnerships. The theory and hypotheses development of this study are discussed in Chapter 5.

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which two or more independent organisations join forces to share and exchange resources, technology or firm-specific assets in the co-development of new products, services or technologies (Gulati, 1998).

[2] Based on the first study, the author presented a paper titled: "Inter-organisational Relationships and Acquisition Likelihood: Evidence from High Technology Firms" at the EURAM, BAM and SMS Annual Conferences (2019) and is grateful to the anonymous reviewers for helpful comments.

In the empirical analysis of the first study, I adopted a case-control design using a matching method called coarsened exact matching (Iacus et al., 2012). The matching method pairs each acquired firm with observationally equivalent targets that could have been acquired (Rogan and Sorenson, 2014). The controls are drawn at random from the population of potential targets and matched on firm size (measured as number of employees), profitability (measured as return on assets) and 4-digit industry SIC codes. The method removes excess heterogeneity, reduces the potential for bias due to confounding factors and leads to a reduction in the variance of the estimated causal effects (Ho et al., 2007). The final sample for the analysis includes 3,798 observations: 477 acquired firms and 1,825 non-acquired firms. A logit model is applied on the matched data set to estimate acquisition likelihood.

The second study focuses on the effect of an acquisition on the innovation performance of acquired firms in relation to their inter-organisational relationships. The innovation performance is measured through two ways: patent output (measured by the number of successful patent applications), and citation output (measured by the number of citations received per patents). This provides insights on the changes in the quantity and quality of output of acquired firms after an acquisition. In the empirical analysis, the issue of endogeneity of an acquisition to acquired firm characteristics that are also correlated with post-acquisition innovation outcomes is dealt with by isolating the exact impact of an acquisition by following the acquired firm before, during and after an acquisition. To take into account the selection bias, coarsened exact matching method is combined with difference-in-differences approach. In this way, the study creates a sample that matched acquired firms with a set of non-acquired firms to observable firm characteristics. A difference-in-difference-in-differences analysis is applied to take into account the influence of pre-acquisition inter-organisational relationships of acquired firms on post-acquisition innovation outcomes. The final sample for the analysis includes 442 acquired firms and 2,982 non-acquired firms. A Poisson regression is applied to estimate post-acquisition innovation performance.

To determine the effect of an acquisition on the innovation performance of merged firms, I analyse changes in patents and citation-weighted patents of the acquiring and acquired firms. The empirical analyses used the same method described above for the second study, combining coarsened exact matching with difference-in-differences analysis. For this study, I created two separate matched samples, one for the acquirers and the other for the targets. This allows to account for characteristics of acquirers that may be correlated with the outcome and makes a sample of matched acquiring firms with a set of non-acquiring firms. For the target firms, I used the same sample used in the previous studies. I then brought the two matched samples of the acquirers and targets together to create a unique sample of matched merged firms with a set of counterfactual acquisitions (non-merged firms). The complete sample for the analysis includes 208 merged firms and 1,095 non-merged firms. An in-depth discussion on the methods and results of the three studies are included in Chapter 6 and 7, respectively.

The results from the analysis suggest the existence of a significantly positive relationship between the two types of inter-organisational relationships examined and the acquisition likelihood. It also brings forward interesting insights on the differences in the acquirer's preference for takeover targets connected by one type of inter-organisational relationship over the other under various conditions. Acquirers tend to favour targets receiving CVC investments over targets engaged in alliances due to the lower interdependence between partners of the CVC-backed firm as compared to a firm involved in alliances that exhibits higher interdependence between partners. Further, as predicted, this relationship is stronger for start-up firms. However, contrary to my expectations, affiliation with high reputation partners weaken the effect of inter-organisational relationships on the acquisition likelihood. I conjecture that this finding reflects acquirer scepticism when potential targets have established relationships with partners with significant bargaining power (Lavie, 2007). Taken together, these findings are consistent with the view that inter-organisational relationships are taken by acquirers as signals of the underlying firm quality when seeking acquisition targets – particularly when their information disadvantage is greater.

The research unlocks a potential source of synergy in acquisitions – inter-organisational relationships of targets. Targets engaged in inter-organisational relationships appear valuable to the acquirers which triggers the transaction. Consistent with the prediction, I find that improvement in post-acquisition innovation activity occurs through operational synergies of the inter-organisational relationships of acquired firms. This suggests that acquired firms with inter-firm linkages result in an increase in innovation output post-acquisition compared to acquired firms that lacked such relationships and conforms to the view of signalling value of the ties. This shows that pre-acquisition inter-organisational relationships of the targets enable managers to better evaluate potential acquisition targets and to acquire relatively more innovative firms. Although inter-firm ties of the targets reduce information asymmetry, adverse selection risk and increase post-acquisition innovation performance of acquired firms, they have an opposing effect on the innovation performance of the combined (acquiring and acquired) firms. This indicates significant challenges to acquirers because it can be quite difficult to manage a broad network and to integrate the targets and their acquired relationships. The results suggest that the signal was effective in conveying information about quality of firms and synergistic benefits of the CVC investments and alliances are found for the acquired firms, but synergies fail to materialize for the merged entities (acquiring and acquired firms) as indicated by a negative effect in the findings. Table 1 provides a brief summary of the dissertation chapters, the primary research questions, research design, sample and findings.

1.3 Contribution to Literature

Theoretically, my dissertation contributes to the M&A and innovation literatures. First, it contributes to the predictive power of the acquisition likelihood model by extending traditional models estimated on the basis of demographic, financial and innovation performance characteristics to include inter-organisational relationships. I explore how the inter-organisational relationships, defined as corporate venture capital investments and alliances, of potential targets influence the likelihood of being acquired. It draws attention to the link between inter-organisational relationships and the signalling effect of visibility and quality (Mazzola et al., 2016). An additional contribution is that the research accounts for both CVC investments and alliances as signals of firm quality and draws a connection between how the different types of ties of firms influence acquirer's choice of potential acquisition target. Prior literature suggests that firms connected by arm's length ties are "impersonal relationships with a focus on self-interested, profit maximizing motives" as pointed out in Uzzi (1996), whereas, alliances can bring in more benefits through knowledge sharing, exchange and learning (Reuer et al., 2012). Corporate venture capital investments tend to be 'distant ties' as depicted by the lower interdependence between the firm receiving CVC investments and the investor. On the other hand, firms engaged in alliances seem to be more deeply involved at the operational level and are likely to know more about the resources and technologies under development (Reuer et al., 2012). The study contributes to an enhanced understanding of the differences in the degree of interdependence between the two types of inter-organisational relationships studied and highlights how these differences shape the acquirer's preference of potential target firms. Firms backed by corporate venture capital investments are characterized by arm's length ties and are more likely to be preferred by acquirers as compared to alliances featuring close relationships. This provides new evidence that both corporate venture capital investments and alliances grant information advantage to acquirers in the M&A market. But the differences in the degree of interdependence between the CVC investments and alliances leads to differences in acquirer's preference of takeover targets.

It further identifies the boundary conditions of the links between such relationships and the acquisition likelihood. These conditions are defined with respect to the interaction between the inter-organisational relationships and the characteristics of target firms and the characteristics of their partners. The research contributes to the existing body of research on

M&A through the finding that the 'visibility-enhancing effect' of inter-organisational relationships on acquisition likelihood is strengthened for start-up firms. The study finds that affiliations with high reputation partners weaken the effect of inter-organisational relationships on the firm's likelihood of being acquired. Prior literature suggests that affiliations with high reputation partners often undermine the bargaining power of the focal firm and restrict its capacity to appropriate value from the value co-created through such collaborations (e.g. Lavie, 2007; Ozmel et al., 2017). Thus, the results reflect perspective acquirers' aversion towards firms which are engaged in unbalanced relationships with high status partners. Second, it enriches knowledge about signals of firm quality, by showing how endorsements of firm quality by third parties can influence acquisition decision making process and perceptions of the managers of the acquiring firms.

This study examines systematically: (1) the extent to which inter-organisational relationships of firms signal quality of potential targets, and (2) how inter-organisational relationships affect subsequent acquisition performance. While prior studies suggest that corporate venture capital investments and alliances are used by acquirers to screen potential acquisition targets (Benson and Ziedonis, 2009; Meschi et al., 2017; Zaheer et al., 2010), this study brings forward the role of corporate venture capital investments and alliances of firms as signals of firm quality to help reduce information asymmetries and adverse selection risk in high technology acquisitions. Previously studies investigated the financial performance of corporate venture capital investments and alliances (Gompers and Lerner, 1998; Porrini, 2004), this research contributes to debate on the relationship between acquisition and innovation performance by taking into account the information benefits conveyed by the inter-organisational relationships of targets.

This study contributes to an important aspect in acquisitions – sources of value creation. It shows how signals can yield benefits by lowering adverse selection risk and how targets with signals perform better after an acquisition than targets that lack signals. Thus, the present research contributes to the signalling value of inter-organisational relationships of firms, particularly, corporate venture capital and alliances. I find that engaging in corporate venture capital investments and alliances overcomes the risk of information asymmetry and adverse selection and increases post-acquisition innovation performance of the acquired firms relative to their counterparts. This means the signal was successful in identifying good quality targets and the signal worked as indicated by the higher innovation performance of the target firms. On the other hand, this study sheds light on the seeming paradox regarding the effect of inter-organisational relationships of the targets on the post-acquisition innovation performance of merged (acquired and acquiring) firms. The combined (acquiring and acquired) firms tend to underperform with the subset of acquired firms which had inter-organisational relationships than those without such relationships. This suggests that even though corporate venture capital investments and alliances may provide informational advantages to acquirers when selecting an acquisition target, such acquisitions incur higher cost of integrating the targets in the merged entities. It shows that careful planning, considerable time and deliberate effort is required to manage the acquisition process in order to realise the gains.

The study contributes to the signalling effect of the inter-organisational relationships, that is, CVC investments and alliances, which may provide valuable information to acquirers as an efficient means of gathering information on firm quality. It takes into consideration the boundary conditions that influence the decision of the acquirer. Finally, the research advances the strategic management literature by examining a potential source of synergy – signals of firm quality.

Table 1.1. Summary of Dissertation Essays

	Study 1: Target Firm Selection Model	Study 2: Acquired Firm Innovation Performance Model	Study 3: Merged Firm's Innovation Performance Model
Research Question	What is the influence of inter-organisational relationships on the likelihood of being acquired?	What is the influence of inter-organisational relationships of firms on the post-acquisition innovation performance of acquired firms?	What is the impact of selecting an acquisition target on the basis of the existence of inter-organisational relationships on the innovation performance of the merged firms (acquiring and acquired)?
Main Hypotheses	**H1a**: Firms receiving CVC investments are more likely to get acquired. **H1b**: Firms engaged in alliances are more likely to get acquired. **H2a**: The effect of receiving CVC investments on the likelihood of being acquired is stronger for start-up firms. **H2b**: The effect of engaging in alliances on the likelihood of being acquired is stronger for start-up firms. **H3a**: The reputation of a CVC investor affiliated with a firm strengthens the effect of receiving CVC investments on the likelihood of being acquired. **H3b**: The reputation of an alliance partner affiliated with a firm strengthens the effect of engaging in alliances on the likelihood of being acquired.	**H4a**: The effect of an acquisition on post-acquisition innovation output is positively related to the number of pre-acquisition CVC investments in a target firm. **H4b**: The effect of an acquisition on post-acquisition innovation output is positively related to the number of pre-acquisition alliances in a target firm.	**H5a**: The effect of an acquisition on post-acquisition innovation output of merged firms is positively related to the number of pre-acquisition CVC investments in an acquired firm. **H5b**: The effect of an acquisition on post-acquisition innovation output of merged firms is positively related to the number of pre-acquisition alliances of an acquired firm. **H6a**: The effect of an acquisition on post-acquisition innovation output of merged firms is negatively related to the number of pre-acquisition CVC investments in an acquired firm. **H6b**: The effect of an acquisition on post-acquisition innovation output of merged firms is negatively related to the number of pre-acquisition alliances of an acquired firm.
Research Sample	• 477 high-technology acquired firms in the U.K. • 2302 acquired and non-acquired firms. • Time period: 2008 – 2016.	• 442 acquired firms in the high-technology sector in the U.K. • 3424 acquired and non-acquired firms. • Time period 2008 – 2016.	• 208 domestic acquisitions of U.K. high-technology firms. • 1303 merged and non-merged firms during the period 2008 – 2016. • UK public acquirers in high technology and non-high technology industries.
Research Design	• A comparison of acquired and non-acquired firms on the basis of similar	• The issue of selection bias is controlled by combining coarsened exact matching with difference-in-differences analysis.	• The problem of selection bias is taken into account by applying coarsened exact matching along with difference-in-differences analysis.

	observable characteristics of firms using coarsened exact matching. • A logit model is applied to estimate acquisition likelihood.	• A triple differences analysis takes into account target selection as a function of inter-organisational relationships of firms on post-acquisition innovation performance of acquired firms.	• A triple differences analysis reveals insights on pre-acquisition inter-organisational relationships of acquired firms on post-acquisition innovation performance of merged firms.
Key Findings	• Of the 477 acquired firms, 139 (29%) are engaged in CVC investments and/or alliances at the time of acquisition. • Firms (a) receiving CVC investments, (b) engaged in alliances increase acquisition likelihood. • Start-ups (a) receiving CVC investments, (b) engaged in alliances are more likely of being taken over. • In contrast to the prediction, affiliations with high reputation (a) CVC investors, (b) alliance partners decreases takeover likelihood.	• Of the 442 acquired firms, 131 (29%) are involved in CVC investments and alliances at the time of acquisition. • Acquisition has a negative impact on the post-acquisition innovation performance of acquired firms. • Acquired firms engaged in inter-organisational relationships, (a) CVC investments, (b) alliances lead to innovation growth after an acquisition compared to acquired firms not involved in inter-organisational relationships.	• Of the 208 merged firms, 64 (31%) acquired firms are engaged in CVC investments and alliances at the time of acquisition. • Negative impact of an acquisition on the innovation output of merged firms after an acquisition. • Decline in post-acquisition innovation performance of merged firms whose targets are engaged in inter-firm ties relative to their counterparts. • Brings forth the importance of (1) the difficulty in managing expanded networks and (2) the time and effort required to manage and retain productive inter-organisational relationships and eliminating less productive ones.

CHAPTER 2

2.1 Introduction

Acquisitions are viewed as an opportunity to achieve cost savings through the exploitation of economies of scale and scope, expansion into new markets, increase in innovation growth and synergistic benefits through complementary resource sharing activities (Capron, 1999; Graebner et al., 2010; Capron et al., 1998). In parallel to the practical relevance of acquisitions, these have captured the interest of scholars in the accounting and finance, economics and strategy literatures as well. Academic scholars have offered interesting insights through various theoretical lenses such as relational perspective, organisational learning and information asymmetry (Rogan and Sorenson, 2014; Meschi et al., 2017; Zaheer et al., 2010; Mazzola et al., 2016). Mergers and acquisitions (M&A) literature highlights two alternative research streams. The first draws upon arguments based on disciplinary takeovers where acquirer's takeover poorly performing firms as compared to their industry counterparts in order to turn them around (Caiazza, Clare and Pozzolo, 2012). The second argument rests upon the resource-based view (Barney, 1991) of the firm that unique synergies arise from a combination of resources and capabilities which are a key driver of acquisitions (Bena and Li, 2014).

In this chapter, I investigate how the various literatures have viewed pre-acquisition inter-organisational relationships from different theoretical perspectives and how signalling theory can contribute to an improved understanding of M&A and acquisition performance outcomes. In doing so, the signalling theory takes a new dimension on the determinants of acquisition likelihood and post-acquisition performance. It contributes to an appreciation of the factors that facilitate acquirer's search for potential takeover targets and identifies conditions when signals are especially most valuable. The following discussion identifies gaps in the literature, considers the role played by signals and adds to little extant knowledge about the contingent value of such signals.

2.2 Why Inter-organisational Relationships Matter: From the Perspective of Strategic Management Theories

The strategic management literature is widely acknowledging the function of pre-acquisition inter-organisational relationships and falls into two categories: studies that examine pre-acquisition relationships between the acquirer and target (Zaheer et al., 2010), and studies that examine the role of target firm relationships (Mazzola et al., 2016). In this research on mergers and acquisitions, the focus is on the influence of inter-organisational relationships of the prospective targets. Such relationships of target firms are an attractive due diligence strategy pursued by acquirers to determine the target firm's quality and prospective synergies (Meschi et al., 2017; Arend, 2004; Hagedoorn and Sadowski, 1999). Firms with inter-organisational relationships can potentially increase the efficiency of the acquirer's search for quality targets (Rogan and Sorenson, 2014), facilitate the choice of acquirers to better understand and learn about the quality of target firms as well as mitigate information asymmetry (Mazzola et al., 2016).

According to the information economics theory, information symmetries are a consequence of sellers knowing better information about themselves than buyers, which causes the economic problem of adverse selection (Akerlof, 1970). Acquisitions research shows that this is a salient reason for failure in acquisitions (Arend, 2004). As target firms hold more information about their own quality relative to the acquirer, it makes it difficult for the acquirer to evaluate the quality of a firm as the acquirer is also aware of the target's ability to misrepresent its true value (Wu et al., 2014). This is exacerbated by the fact that the value of high technology firms depends more on what is in the pipeline than on the products which have already reached the market which makes buyers more cautious about purchasing target firms for which they cannot see the goods even though the targets realize the full value of their company (Dierickx and Koza, 1991). Specifically, the study by Balakrishnan and Koza (1993) demonstrates the importance of the costs associated with the transfer of ownership rights when relevant assets are non-homogeneous and lack complete information or knowledge about their quality, performance and value.

This information asymmetry problem can have two outcomes, (1) the acquirer is likely to make an adverse selection and (2) overpay for a prospective target and subsequently affect the outcome of an acquisition. Inter-organisational relationships of the target firms may reveal additional valuable information about its underlying quality and enable acquirers to distinguish between high quality and low quality firms (Mazzola et al., 2016; Akerlof, 1970). Studies analysing the influence of inter-organisational relationships of firms in the context of IPOs have shown that a firm's interfirm ties provide endorsements and influence perceptions about quality of firms (Stuart et al., 1999; Stuart, 2000). This lowers information asymmetry, overcomes the risk of adverse selection (Arend, 2004; Rogan and Sorenson, 2014) and offers effective evaluations of the target firms to materialise synergies from an acquisition.

From the view of the organisational learning literature, inter-organisational relationships allow firms to exchange and share knowledge about resources, assets and capabilities (Anand and Khanna, 2000; Zaheer et al., 2010; Hamel, 1991). Such relationships can create access to deal flow and convey valuable information (Sorenson and Stuart, 2008). The social network perspective suggests that a firm's direct relationships in terms of collaborations develop and strengthen its standing compared to other firms in a social structure (Gulati, 1995). To add to this insight, a firm's engagement in inter-organisational relationships locates it in network positions that enable it to keep pace with the most promising scientific or technological developments (Powell, Koput and Smith-Doerr, 1996). These inter-firm relationships play a critical role in allowing firms to stay abreast of rapidly changing developments (Gulati, 1998). A higher degree of interaction or involvement in inter-organisational relationships enriches a firm's ability in managing relationships, fosters experience at cooperation and a firm accomplishes reputation as a partner (Powell et al., 1996). Experience with a diverse range of collaborative networks is an additional proof that a firm is versatile and is well connected to other firms in a network (Gulati, 1995). Firms with more inter-organisational relationships are more experienced as their ties provide more central connectedness, timely access to knowledge, assets and financial resources (Katila, Rosenberger and Eisenhardt, 2008). Increasing collaborations broadens a focal firm's horizon, as it accumulates information about opportunities and obstacles, develops awareness about potential projects that might be undertaken and opens it to prospective partners (Gulati, 1998; Powell et al., 1996). This is likely to positively influence the perceptions of an acquirer.

According to the social capital literature, the central connectedness of a focal firm enhances visibility (Mazzola et al., 2016), provides a window on technological resources (Benson and Ziedonis, 2009) and information-rich networks (Gulati, 1995; Powell et al., 1996). The real options theory views a firm's inter-organisational relationships as a series of options or staged investments to gather knowledge about the value of a firm, its resources and activities which is otherwise unknown and is deemed desirable under uncertain conditions (Tong and Li, 2010; Brouthers, Brouthers and Werner, 2008). From the relational perspective, firms are likely to bond over similar characteristics and interests as increasing similarity lowers trust asymmetries and provides better access to information about quality of potential exchange partners (Rogan and Sorenson, 2014). Further to this, having inter-organisational relationships informs the resource-based theory such that they can provide access to resources that are unique, valuable and difficult to imitate (Barney, 1991). A firm with a higher number of alliances is sought after by acquirers because of the valuable resources and knowledge that it can share with its partners (Wang and Zajac, 2007; Hagedoorn and Sadowski, 1999). Nicholson and colleagues (2005) suggest that alliances are seen as a signal of asset and firm quality. This allows acquirer's information advantage when the value of a potential target firm cannot be comprehended.

Each of the theories discussed above hold important significance and relevance in the literature. A critical aspect in M&A is that imperfect information between acquirers and targets can lead acquirers to select an inappropriate target firm for an acquisition. With regards to this, the signalling mechanism provides a complementing perspective to overcome the problem of information asymmetry and the risk of adverse selection inherent in the phenomenon of acquisitions. According to the signalling theory, information about the quality of products is carried by signals that enable buyers to differentiate between high quality and low quality products (Spence, 1973; Bergh et al., 2014; Connelly et al., 2011). This research argues that the signalling mechanism allows acquirers to mitigate the information asymmetry problem, adverse selection risk and identify quality takeover targets. This forms the theoretical lens of my research and the following section explains why signalling mechanism is a suitable framework to investigate the context of high technology acquisitions and how it can bridge the gaps in the literature.

2.3 Signalling Theory

According to information economics literature, sharing equal information between the parties involved in a transaction forms the foundation of an efficient information exchange. This condition is an uncommon practice as the sellers possess superior information about the quality of their products and buyers cannot discern differences in the quality of a product prior to purchase (Akerlof, 1970). The information constraints on the quality of products create difficulties to accurately assess a particular purchase as the sellers also have the incentive to misrepresent their true quality and provide buyers with exaggerated claims about its capabilities and prospects (Wu et al., 2014). This information asymmetry problem can have two parallel consequences: (1) the risk of adverse selection, and (2) the seller encounters a 'credible signalling problem' (Dierickx and Koza, 1991). In the presence of incomplete information, the problem of adverse selection makes it difficult for the buyer to arrive at a suitable evaluation of its purchase.

Spence (1973) furthers the discussion by Akerlof (1970) to resolve the problem of information asymmetry by observing signals which is presented in the signalling theory. According to the signalling mechanism, information between two parties, in an equilibrium medium, is transmitted in the form of signals that indicate quality through characteristics which are costly and difficult to imitate (Spence, 1973, 2002). The signals allow buyers to distinguish between high quality products and low quality products, thus reducing information asymmetry and adverse selection problem (Bergh et al., 2014; Connelly et al., 2011).

Signalling theory has been studied in a wide variety of contexts, for example, new product introductions (Akerlof, 1970), labour markets (Spence, 1973) and initial public offerings (Reuer and Ragozzino, 2008; Reuer and Ragozzino, 2012; Pollock, Chen, Jackson and Hambrick, 2009). More recently, it has gained traction in the M&A literature (Mazzola et al., 2016). Research on M&A has studied the determinants of acquisition premium via the signalling perspective (Reuer, Tong and Wu, 2012). However, the determinants of acquisition likelihood and post-acquisition outcomes deserves more attention. It is also worthwhile to examine the interaction effect of signals with the characteristics of the sellers which has received less consideration in the literature on the determinants of acquisition likelihood. For example, studies have tested that IPOs are valuable signals and increase the likelihood of post-IPO acquisitions (Mazzola et al., 2016; Ragozzino and Reuer, 2007). Prior studies suggest that there is considerable scope in the literature to explore M&A further, and applying information economics and signalling mechanism (Akerlof, 1970; Spence, 1973) can offer interesting insights on the search process and explain target firm selection mechanism. Another aspect of M&A is to create value from an acquisition which has been considered from various theoretical perspectives. There remains an opportunity in the literature for a deeper discussion on the relation between signals and acquisition performance. By conducting this research, I investigate the broad potential of signalling mechanism in the context of high technology acquisitions.

2.4 Choice of Target Firm: A Signalling Mechanism

Building on signalling theory, the phenomenon of mergers and acquisitions can be regarded as an information asymmetry problem. The target firms hold better information about their own quality than the acquirers prior to an acquisition. The imperfect information between the acquirers and targets complicates the matter as the acquirer cannot differentiate between a good quality target and a poor quality target. This problem of information asymmetry leads to: (1) the risk of adverse selection, and (2) the target firm also faces a credibility problem in providing acquirers information about their value because the value potential for high technology firms is contingent on the products under development or a target firm's technological prowess (Akerlof, 1970; Dierickx and Koza, 1991). Even though the target firm is aware of its true quality, their inability to provide evidence of their forthcoming inventions to the acquirers (Wu et al., 2014), introduces uncertainty into acquirer's belief about the quality and future prospects of a particular target firm. To overcome the information disadvantage, acquirers can rely on the information conveyed by signals which can yield benefits in identifying superior quality acquisition targets and facilitate M&A transactions (Spence, 1973, 2002; Ragozzino and Reuer, 2007).

In this research, I argue that inter-organisational relationships of firms serve as signals of firm quality, lower the effects of information asymmetries in the M&A market and mitigate the risk of adverse selection (Akerlof, 1970; Spence, 1973, 2002). The signals enable acquirers to distinguish between high quality firms and low quality firms to make a better selection and gain synergies from the partnership. Firms search for signals of firm quality when information is harder to access on potential target firms and represent an important means for acquirers to gather valuable information before making acquisition decisions (Mazzola et al., 2016). This study hopes to provide fresh insights on acquisitions of high technology firms informed by the signalling perspective and to propose avenues for improving target firm selection by examining factors that might make a firm an attractive acquisition candidate.

In examining whether collaborations increase the subsequent likelihood of an acquisition, acquirers observe signals from inter-organisational relationships of firms, that is, corporate venture capital investments and alliances. As the number of CVC investments and/or alliances of a firm increase, it gains more visibility which signals its quality to an acquirer, makes the information asymmetry and adverse selection problem less severe (Mazzola et al., 2016; Koka and Prescott, 2008; Ozmel, Reuer and Gulati, 2013). Firms involved with greater number of CVC investors and/or alliance partners shows that the firm is able to manage a diverse portfolio of relationships (Gulati, 1995, 1998). Studies emphasizing the role of interorganisational ties suggest the importance of such networks in gaining information, flexibility and resource benefits that are likely to enhance firm performance (Ozcan and Eisenhardt, 2009). Additionally, firms can also benefit from the operating synergies of their ties and adding multiple simultaneous ties increases the firm's value (Ozcan and Eisenhardt, 2009) and visibility to prospective acquirers. Other advantages of firms involved in networks suggest that key scientists and inventors can manoeuvre within networks and be inventive and reflective in their network actions and so improve their portfolios (Hallen, 2008). Such ties bring additional benefits such as access to superior resources (Powell et al., 1996). Research also shows that the prior interaction between the partners can influence a tie's effectiveness as partners are better able to work together and so achieve the benefits of ties through greater trust, cooperation, communication and coordination (Agarwal et al., 2012). Studies also demonstrate that increasing number of ties can positively influence performance (Powell et al., 1996; Ahuja, 2000; Stuart, 2000) as partners that compete with each other improve focal firm performance by enhancing the bargaining power facing these partners (Lavie, 2007).

The signalling mechanism highlights the role of information transferred by signals which are costly and difficult to imitate (Spence, 1973; Bergh et al., 2014; Connelly et al., 2011). By relying on the information conveyed by the signals, the acquirers are able to identify prospective firms to takeover. Inter-organisational relationships serve as positive signals for acquirers and influence their perceptions about the quality of a particular firm. In acquisitions, the conditions based on the characteristics of the target firms or those of its partners is likely to impact the acquirer's decision to acquire. Even though the search for a prospective target occurs early in the process of acquisition, the success or failure of acquisitions is ultimately determined by the selected target firm (Wu et al., 2014). Selection of an inappropriate target can subsequently lead to integration difficulties and eventually fail to generate intended synergies from an acquisition. The next section presents an overview of the acquisition and innovation performance literature.

2.5 Impact of M&A on Firm Performance

Synergy is a key proposition in the strategic management literature and exists when the value of the combined business is greater than the sum of the individual values of the two combining businesses (Seth, 1990). In acquisitions, synergies exist when the excess value between acquiring and acquired firms exceeds the sum of their standalone values, that is, Value (A, B) > Value (A) + Value (B) (Seth, 1990). The extant literature offers insights on how acquisitions affect innovation performance and whether they create value. Research on innovation performance captured by the degree of technological overlap (measured by number of patents granted in technology class) between merging firms found positive effect of an acquisition emphasizing technological synergies as major drivers of M&A (Bena and Li, 2014; Sears and Hoetker, 2014; Cassiman et al., 2005). High technology acquisitions tend to create value when the technological knowledge is similar enough to provide learning opportunities but different enough to provide acquirers with new knowledge (Ahuja and Katila, 2001; Cloodt et al., 2006; Makri et al., 2010). Economic performance captured by cumulative abnormal returns to acquirers gain from an acquisition if they exert greater control over resources and have more bargaining leverage compared to its target (Capron and Pistre, 2002). In such cases, the acquirers have a wider selection of target firms to choose from which lowers competition from other potential bidders (Capron and Pistre, 2002). If, however, target firms have a bargaining leverage as multiple bidders are likely to compete to gain access to these resources, information asymmetry between competing bidders renders access to target's resources difficult and causes disruption of target firms post-acquisition (Capron and Pistre, 2002).

On the other hand, research has shown that acquirers are unable to materialise synergies and that the benefits accrue to the target firms' shareholders. The negative outcomes of an acquisition on innovation performance have been attributed to diversion of managerial time and effort away from the R&D process (Hitt et al., 2001); disruptions in organisational routines and processes, decline in R&D investments and acquired firm's employees exit the firms (Puranam et al., 2006). Research linking acquisitions and innovation performance finds negative outcomes on the innovation inputs (measured as R&D and R&D intensity growth), output (measured by patents) and productivity (measured as patents to R&D intensity growth) of merged firms compared to non-merged firms (Ornaghi, 2009). Innovation performance captured by R&D intensity (measured as R&D expenditure to total assets) and R&D productivity (measured as number of successful patent applications to R&D expenditure) tend to decline after acquisition (Desyllas and Hughes, 2010). This reflects the restructuring costs, disruption of R&D organisation and routines (Desyllas and Hughes, 2010). Too much technological similarity between the acquiring and acquired firms also shows negative effect of an acquisition on post-acquisition innovation performance (Colombo and Rabbiosi, 2014). Even though previous research has highlighted important theoretical and empirical contributions of the effect of acquisitions on innovation performance, the influence of pre-acquisition inter-organisational relationships on post-acquisition innovation performance needs to be investigated.

2.6 Research Gap

The extant literature on mergers and acquisitions (M&A) and inter-organisational relationships highlights two arguments. The first focuses on the choice perspective that firm characteristics are a determinant of acquisition likelihood and outcomes. The second argument pays attention to different governance mechanisms – choice between M&A versus alliances (Wang and Zajac, 2007) and how the governance choice materialises synergy by measuring impact on firm performance (Castaner et al., 2014). However, the effect of target inter-organisational relationships as a determinant of acquisition likelihood has received limited consideration. Further, how synergies are realised in such relationships and how this affects post-acquisition success is relatively under-researched. My research contributes to the first view, that is, the choice perspective which examines characteristics of firms that determine acquisition probability and outcomes.

Prior research has focused on common clients between acquirers and targets (Rogan and Sorenson, 2014), pre-acquisition relationships between acquirers and targets (Meschi et al., 2017; Khan, 2016; Zaheer et al., 2010; Al-Laham et al., 2010; Porrini, 2004) and the inter-organisational relationships existing in an acquiring firm's portfolio (Benson and Ziedonis, 2009). However, the question of whether a target firm's inter-organisational relationships affect acquisition likelihood and success have not been investigated extensively. This is an important distinction between this study and those covered in the earlier works. By undertaking this research, I aim to fill this minute yet important gap in the literature. The immediate relevance of this gap is substantiated by the fact that previous studies examining common partners, shared suppliers or common clients between acquirers and targets take either a relational perspective on acquisitions to identify promising acquisition targets and assess success of an acquisition (Rogan and Sorenson, 2014). Or, research analysing the prior relationships between the acquirer and target view this as a screening mechanism to select acquisition targets and evaluate post-acquisition performance outcomes (Meschi et al., 2017; Zaheer et al., 2010; Al-Laham et al., 2010; Porrini et al., 2004; Benson and Ziedonis, 2009). This literature highlights the problems associated with selecting acquisition targets such as information asymmetries between acquirer and targets lead to the selection of poor quality targets or the biases arising because of the favourable initial beliefs and expectations about potential partners cause inappropriate acquisition decisions (Meschi et al., 2017).

The role of inter-organisational relationships of firms in identifying promising acquisition targets via signalling mechanism is an interesting area of research that has been overlooked. I investigate the influence of inter-organisational relationships of potential target firms through the lens of the signalling theory. The study examines inter-organisational relationships as 'visibility-enhancing' signals. It suggests that as a firm's direct inter-organisational ties increase, the firm becomes more visible and 'stands out from the crowd' (Pollock and Gulati, 2007; Gulati and Higgins, 2003). This mitigates the risk of information asymmetry between the acquirer and target and the risk of adverse selection and facilitates acquirers to evaluate the quality of potential target firms. This research aims to investigate inter-organisational relationships of firms as signals that separate high quality firms from low quality firms in the decision-making process entailing M&A and whether such acquisitions are able to create synergies for the targets and the merged (acquiring and acquired) entities. The theoretical frame based on signalling perspective provides fresh and valuable insights about target firm selection mechanism by analysing the quality of firms as documented in their inter-organisational relationships.

Studies analysing the incidence of acquisition focus on demographic, financial and accounting, economic performance, innovation-related and prior relationship (between acquirer and target) characteristics of firms (Palepu, 1986; Powell, 1997; Hasbrouck, 1985; Morck, Shleifer and Vishny, 1988; Dickerson, Gibson and Tsakalotos, 2002; Desyllas and Hughes, 2009; Hall, 1999; Meschi et al., 2017). However, they do not account for acquisitions of targets engaged in inter-organisational relationships which are also important characteristics of firms. In my knowledge, only Mazzola et al. (2016) investigate acquisition likelihood of firms engaged in direct ties but their study defines interfirm agreements consisting of unilateral contracts, bilateral alliances, minor equity alliances, joint ventures and M&A. My research extends the trajectory initiated by Mazzola and colleagues and investigates the influence of inter-organisational relationships of firms on the choice of acquisition target. In my study, I define inter-organisational relationships as corporate venture capital investments and alliances. The primary motivation for studying CVC and alliances is that technology firms exhibit both. CVC and alliances have been used by acquirers as a due diligence strategy to search for superior quality takeover targets. But prior work has considered the influence of these two types of inter-organisational relationships on acquisition likelihood independently. Also, very little is known about how CVC and alliances shapes acquirers' acquisition decisions. I conjecture that the acquirer's decision to takeover firms can be influenced by CVC and alliances simultaneously. Moreover, the nature of this influence depends on a variety of boundary conditions. I seek to bridge this gap in the literature by studying how CVC and alliances guide acquirers' acquisition decisions. The work unpacks relationships and discriminates between alliances and CVC investments to increase understanding about how the two types of inter-firm partnerships differ in their effects on acquisition. Thus, my work advances strategy research by uncovering the role of CVC investments and alliances as signals of firm quality in directing firms' acquisition decisions.

Moreover, Mazzola et al (2016) take into account only a few conditions that might influence acquisition likelihood. They study the relationship between direct ties of a firm and prominence on the likelihood of being acquired when a firm undergoes an IPO. I explore additional conditions in my research work that might interact with the inter-organisational relationships considered and how acquirers preferences vary under those conditions. Further, whether acquisitions with signals outperform those that lack signals is a relevant gap and a considerable area of interest in the strategic management literature (Wu et al., 2014). By conducting this research, I endeavour to fill this important gap in strategic management research and demonstrate the impact of inter-organisational relationships of firms on the post-acquisition innovation outcomes. I first examine the effect of inter-organisational relationships of firms on innovation performance of acquired firms after an acquisition. I then investigate the impact of inter-organisational relationships of acquired firms on the combined (acquiring and acquired) firms innovation performance post-acquisition. The research attempts to illustrate the importance of signals and their role in value creation.

The findings of the study by Mazzola et al (2016) are limited to a sample of firms in the biopharmaceutical industry which cannot be generalised to other industry sectors. I conducted my research on high technology firms which are defined by Hall and Vopel (1996) as firms with primary activity in SIC 28, 35, 36, 37, 38, 48, 73 and 87. This allows me to cover a broad variety of industries and gives interesting insights. In addition, the authors model the choice of a target through a logit model and do not control for the possible selection bias that could arise due to the characteristics of acquired and non-acquired firms that may also be correlated with the outcome (Mazzola et al., 2016). An important feature addressed in my research is that it considers characteristics of both acquired and non-acquired firms by applying a matching methodology that compares observable characteristics of both acquired and non-acquired firms (Iacus et al., 2012). In this way, the study controls for factors that could be omitted in the choice of target (Rogan and Sorenson, 2014). I further study the acquisition outcomes of firms engaged in inter-organisational relationships and add to extant knowledge by showing how acquired firms enhance innovation output through their inter-organisational partnerships. The acquisition performance effects are also analysed for the merging firms and the role played by the inter-organisational relationships of acquired firms. This study uses difference-difference-in-differences technique (Wooldridge, 2009) with a combination of coarsened exact matching (Iacus et al., 2012) which provides a better estimation of causal effect of the treatment effect. Previous studies do not address this, for example, Porrini (2004) analysed a sample of acquisitions of pre-acquisition alliances only.

Moreover, most of the studies use accounting performance such as return on assets and cumulative abnormal returns to measure the post-acquisition performance (Porrini, 2004; Benson and Ziedonis, 2009; Zaheer et al., 2010). An efficient method of measuring post-acquisition performance of technology intensive firms is to look at innovation performance (Cloodt et al., 2006). Innovation performance is measured using patents and citations data as patents represent that an invention is novel, useful and not obvious, and when an invention is brought to the market, then it becomes an innovation. The literature frequently measures innovation performance by using both raw counts of patents and citations (Bena and Li, 2014; Seru, 2014; Ahuja and Katila, 2001; Cloodt et al., 2006). Considering this context, patent and citation output can be a reasonable and acceptable indicator of innovation output. An advantage of using patent and citations data is the invaluable information it provides on productivity and novelty of inventions and can be used as an effective measure of innovation performance (Cloodt et al., 2006). Using patent and citations data has drawbacks too as all firms might not have patents and a considerable amount of time is elapsed by the time patents begin to receive citations (Hall et al., 2005). This research aims to investigate innovation performance following an acquisition and the sources of innovation are measured through patenting activity and citation output as synergies are realised when there are positive changes in patent and citation output.

CHAPTER 3

Inter-organisational Relationships and Acquisition Likelihood

3.1 The Likelihood of Being Acquired

A central question in strategy research is about predicting takeover targets (Claussen et al., 2017; Desyllas and Hughes, 2009; Caiazza et al., 2012). In response, researchers have identified the role of demographic, financial and accounting variables, economic performance and innovation related characteristics of firms that make them a desirable acquisition target (Hasbrouck, 1985; Danzon et al., 2007; Hall, 1988). Prior studies have looked at operating profit, total assets, market-to-book ratio, liquidity and leverage as significant predictors of acquisition likelihood (Palepu, 1986; Powell, 1997). However, these studies do not take into consideration the role of inter-organisational relationships of targets, such as, alliances and CVC which may also be important predictors of the likelihood of being acquired.

Previous research has shown that small firms were more likely of being acquired because of the low costs associated with the absorption of small targets into the acquirer's organisation (Granstrand and Sjolander, 1990). This research lacks a clear explanation about how the quality of firms is assessed which may affect acquisition likelihood. Further to this, prior research work on target firm characteristics provides mixed evidence on pre-acquisition performance of the targets. Economic performance indicates the degree of success in the market place and extant research argues that turning around poorly performing firms is a likely motive of acquisition (Morck, Shleifer and Vishny, 1988; Dickerson, Gibson and Tsakalotos, 2002). However, the results of the study by Agrawal and Jaffe (2003) suggest that targets were better performers and only a small fraction of all takeovers are likely to include poorly performing firms. These studies look at a limited number of indicators of firm quality and call for further investigation of more reliable indicators of firm quality that may also affect acquisition likelihood.

Prior research has examined the innovation related characteristics of firms and suggests that targets exhibited low pre-acquisition patent intensity and R&D intensity compared to non-acquired firms (Desyllas and Hughes, 2009; Hall, 1999; Hall et al., 1990). However, this does not give a complete picture of all of the characteristics of firms considered. These are some of the characteristics of firms that affect acquisition likelihood, to name a few. To gain a more holistic understanding of the characteristics of targets that affect acquisition likelihood, additional characteristics of targets such as alliance and CVC relationships may also need to be taken into account.

The acquisition likelihood has also been examined with respect to direct relationships between acquiring and acquired firms. For example, Cisco Systems forms alliances with firms or uses small equity investments as a 'real option' to gain information on products under development and to identify potential acquisition targets. Thus, pursuing a dual growth strategy enabled Cisco to grow by an average of 36% to 44% in the years 1993 – 2003 (Dyer, Kale and Singh, 2004). On the other hand, common connections between acquirers and targets, through common clients, shared suppliers, service providers or hiring employees of competitor firms allows buyers to gain access to private information to make more reliable assessments on strengths and weaknesses of potential acquisition targets, and costs associated with picking a poor quality acquisition target (Rogan and Sorenson, 2014). Such relationships expose buyers to prospective takeover targets in close geographical proximity and similar interests or characteristics which strengthens trust, lowers information asymmetry and the risk of adverse selection at the same time (Schildt and Laamanen, 2006; Zaheer et al., 2010; Meschi et al., 2017). Another complementing study by Mazzola, Perrone and Kamuriwo (2016) examines the role of direct ties of a firm and its network position on the likelihood of an acquisition in the biopharmaceutical industry. Their findings suggest that interfirm agreements serve as 'visibility-enhancing signals' that facilitate likelihood of an acquisition.

Although all these studies are important contributions, our understanding of the likelihood of being acquired has been primarily restrained on the impact of firm-specific characteristics on the acquisition likelihood. Especially missing from extant work is a framework to inform the question of whether and under what conditions inter-organisational relationships of firms influence a firm's likelihood of being acquired.

3.2 The Role of Inter-organisational Relationships

The aim of my research is to investigate whether inter-organisational relationships, namely, corporate venture capital investments and alliances provide valuable signals of firm quality to the acquirers to make superior choices, relative to other acquiring firms, among the options that are available to them. Previous studies on inter-organisational relationships have defined these as equity investments in firms and strategic alliance partners of firms (Stuart, Hoang and Hybels, 1999). More recent literature has included corporate venture capital (CVC) investments as inter-organisational relationships (Dushnitsky, 2012). For this study, I define inter-organisational relationships as corporate venture capital investments and alliances collectively. This definition encompasses a broad set of inter-firm ties and coincides with those used in empirical studies on inter-organisational relationships (Gulati, 1995; Dushnitsky and Lenox, 2005a, 2005b). CVC investments are defined as minor equity investments pursued by established corporations that extend their corporate venture capital arm to invest in entrepreneurial firms seeking capital for growing its operations (Dushnitsky, 2012; Gompers and Lerner, 1998). Alliances are defined as voluntary cooperative agreement in which two or more independent organisations join forces to share and exchange resources, technology or firm-specific assets in the co-development of new products, services or technologies (Gulati, 1998; Vanhaverbeke, Duysters and Noorderhaven, 2002).

In order to understand the role of each of the inter-organisational relationships considered, it is imperative to take into account the similarities and differences between the two. An important common feature of both corporate venture capital investments and alliances is that both are inter-organisational relationships which increase the observability, lower information asymmetry, reduce adverse selection risk and signal quality of firms (Mazzola et al., 2016). Both corporate venture capital investments and alliances are established to develop competing technologies in entrepreneurial firms (Dushnitsky and Lenox, 2006; Graebner et al., 2010; Stuart, 2000). For example, Google launched a CVC program called Google Ventures to invest in entrepreneurial firms or start-ups like Adimab (Dushnitsky, 2012) which used the investment for antibody drug discovery. Similarly, Apple formed alliances with EMI, Google, Salesforce.com, Microsoft among many others (Ozcan and Eisenhardt, 2009) to create breakthrough technological products. Additionally, research suggests that firms backed by CVC investments contribute to innovation by producing more inventions from each dollar invested (Graebner et al., 2010) and firms connected in alliances increase innovation growth (Stuart, 200). Among the different types of alliances, an equity alliance shares a common characteristic with CVC activity, that is, both alliances and CVC serve as resource sharing and exchange mechanisms for two independent firms (Dushnitsky, 2012). Apart from this, most alliances do not involve equity, with joint ventures drawing major equity stakes from the partners that directly influence the operations of the new venture (Vanhaverbeke et al., 2002).

The key differences between CVC investments and alliances lie in the activities and financing of operations in firms. A key ownership feature of a CVC investment in an entrepreneurial venture is that it enables the corporate investor to exert influence on its corporate decisions (Dushnitsky, 2012). In alliances, both partners make financial investments and share the risk and gains from their collaboration (Vanhaverbeke et al., 2002), whereas, CVC investment entails the flow of capital from the corporate investor to the entrepreneurial firm (Dushnitsky, 2012). Alliances involve engagement of both partner firms and the activities are performed interactively (Hamel, 1991). In contrast, CVC investment involve that the entrepreneurial firm performs all operations independently (Dushnitsky, 2012). The choice between CVC investments and alliances also differs in terms of commitment. Alliances involve greater commitment and may be preferred in industries that demand greater commitments for working on projects or that experience higher conditions of uncertainty. The flexibility of CVC investments allows firms to take advantage of changed circumstances and can be reversed in case when large investments are too risky (Basu, Phelps and Kotha, 2011 and Van de Vrande, Vanhaverbeke and Duysters, 2009). The two also differ in the level of interdependence, where, alliances are characterised by a higher level of interdependence (Vanhaverbeke et al., 2002) as compared to CVC investments. In terms of CVC investments, these are more likely to work as an option as they reduce uncertainties associated in high technology acquisitions (Tong and Li, 2011). These differences are likely to affect acquisition decisions for firms engaged in the two different types of inter-firm relationships and are also likely to differ in terms of the conditions under which acquisitions are examined.

3.2.1 Corporate Venture Capital (CVC) Investments

In order to study the relationship between CVC and acquisition likelihood, it is important to understand the objective of pursuing CVC investments. The literature offers varying explanations of why established firms invest in new ventures. While some firms pursue financial objectives from a CVC, others seek strategic objectives, yet some evidence suggests that CVC investors attempt to pursue both objectives (Chesbrough, 2002). As reported by the findings of Siegel et al. (1988), the most important objective of a CVC program is to gain "return on investment". This is followed by strategic objectives which include "exposure to new technologies and markets" as the second important objective. Other strategic objectives include "potential to manufacture or market new products" and "potential to acquire companies". Other studies also suggest a similar order of importance of objectives of pursuing CVC investments (Benson and Ziedonis, 2010; Hellman, 2002). Strategic investors opt for CVC investing when returns or success of a project is more important than the strategic benefit (Arping and Falconieri, 2010) which suggest the element of arm's length relationships. A strategic objective to pursue corporate venture capital investments might be to select an acquisition target (Skyes, 1990); while other studies suggest that it is not the objective of CVC to identify acquisition opportunities (Winters and Murfin, 1988); yet some other studies find that a CVC-acquisition relationship can differ across types of CVC programs (Siegel et al., 1988).

CVC investments are viewed as ‘real options’ and firms pursue them in times of higher level of uncertainty due to their reversible nature (Tong and Li, 2011). The CVC-investing activities of firms provide a ‘screening mechanism’ to identify potential acquisition targets and firms with more stable CVC programs earn higher returns (Benson and Ziedonis, 2009). It provides a variety of information and are regarded as ‘window on new technologies’, accrue learning benefits and promotes trust among firms (Dushnitsky and Lenox, 2005a, 2005b, 2006). Drawing on a sample of acquisitions of 530 entrepreneurial firm takeovers by 61 CVC investors, Benson and Ziedonis (2010) find that only 89 entrepreneurial firms were backed by the acquirers. Additionally, their research finds find positive abnormal returns of 0.67% to acquirers of non-portfolio companies and negative acquirer returns of -0.97% for acquiring a CVC portfolio company. This suggests that CVC investors commonly acquire non-portfolio ventures backed by other CVCs. The dissertation thesis by Dimitrova (2013) complements the above research and finds that CVC investors experience on average significant negative abnormal return of -0.60% when they acquire portfolio companies (but not when they acquire non-portfolio CVC-backed ventures) which stems from CVC acquirer’s poor internal innovation and high dependence on external innovation. This suggests that outside corporate bidders are more likely to acquire a non-portfolio venture, to pre-empt the potential competition from invested CVCs. Entrepreneurial firms that receive CVC-backing are particularly vibrant sources of technological innovation and new products and produce significantly more inventions per investment dollar than other firms in related industries (Graebner et al., 2010). This makes them attractive acquisition targets as it signals firm quality and increases likelihood of being acquired. As the number of CVC investments in a firm increase, it gains visibility and signals the quality of firms to the acquirer which reduces information asymmetry and the problem of adverse selection risk (Ozmel et al., 2013; Mazzola et al., 2016). Consequently, the signalling effect of CVC investments increases a firm's visibility and conveys valuable information to the acquirers which allows them to distinguish between high quality firms and low quality firms and increase a firm's likelihood of being acquired.

Hypothesis 1a: Firms that receive CVC investments are more likely to get acquired.

3.2.2 Alliances

Alliances are defined as cooperative effort between firms to work together on a project by pooling resources to achieve a common strategic goal and can offer valuable information exchange (Vanhaverbeke et al., 2002). Alliances are a type of inter-organisational relationship of firms that help alleviate information asymmetry and adverse selection in the M&A market and provide important information about acquisition opportunities (Mazzola et al., 2016). Having alliances are useful signals of firm quality which enable buyers to differentiate between attractive and unattractive targets (Shen and Reuer, 2005). This information carried by signals reduces valuation problems, perceived risk and uncertainty about firm quality to external parties and influences takeover likelihood (Hoehn-Weiss and Karim, 2014).

Prior alliances can function as a driver of future alliance formation because it decreases cost of searching for alliance partners (Chung et al., 2000). This argument can be extended to the acquisitions literature that pre-acquisition alliances of targets lower the search costs incurred by acquirers, help them to find the right partner and are likely to trigger acquisitions. Social relations create trust that can lower the potential moral hazard related to acquisitions (Schildt and Laamanen, 2006). Another research analysing inter-organisational collaboration in biotechnology industry between 239 new ventures and 156 established companies suggests that firms that gained prominent positions in networks of firms signal quality and prospects of firms and facilitate future collaborations (Ozmel, Reuer and Gulati, 2013). When the quality measure of targets is ambiguous, the quality of a firm is dependent on the alliances of a focal firm (Chung et al., 2000). These are perceived as signals of firm quality by the external parties and are more likely to affect target firm selection. Thus, the signalling effect of alliances encourages acquirers to takeover firms when there is ambiguity on firm quality and a focal firm lacks visible indicators of firm quality.

Firms with increasing number of alliances contribute to innovation growth (Stuart, 2000) and an increase in the number of alliances of a focal firm means an increase in opportunities to commercialise technologies (Arora and Gambardella, 1990). This conveys valuable information about the future potential of promising acquisition targets. Such relationships act as an endorsement (Stuart et al., 1999) which signals quality of firms and positively influences acquisition likelihood. Accordingly, as the number of alliances of a focal firm increase, it gains visibility and allows firms to 'stand-out from the crowd' (Pollock and Gulati, 2007). Thus, the 'signalling-effect' of alliances provide information to acquirers about the quality of a prospective target firm, lower information asymmetry and adverse selection risk, and increase a focal firm's likelihood of being acquired.

Hypothesis 1b: Firms engaged in alliances are more likely to get acquired.

3.3 When are Signals Most Valuable? The Conditions Affecting the Value of Signals

The value of a signal is likely to depend on certain conditions that influence the choice of an acquirer. For example, signals are valuable for exchange partners or potential investors when targets are young companies (Stuart et al., 1999) as there is ambiguity about their quality. For established firms, the risk of adverse selection is less severe as they have developed some track record of information and similar signals might not have the same advantage (Wu et al., 2014). Likewise, research illustrates that newly public firms are more likely of being acquired as compared to private firms because when a firm goes public, it reveals information about its performance, key analysts and investors (Arikan and Capron, 2010; Reuer, 2005). Similarly, studies have shown that affiliations with prestigious venture capitalists or high reputation investment banks act as signals and are likely to raise the acquisition premiums of IPO targets

(Reuer et al., 2012). The importance of signals has been studied under different market conditions, for instance, a young firm's connections with prominent venture capitalists influence success of an IPO in cold markets where as connections with reputable investment banks play a role in IPO success in hot markets (Gulati and Higgins, 2003).

I further theorise that while inter-organisational relationships increase the visibility and serve as signals of firm quality, their propensity to affect an acquirer's decision to takeover a focal firm will be moderated by two boundary conditions. I investigate these through the interaction effects between inter-organisational relationships and target firm characteristics or its partners on acquisition likelihood. Only Mazzola and colleagues (2016) have examined the interaction effects between inter-organisational relationships and IPOs on the likelihood of being acquired. This research attempts to take into consideration additional conditions that may also affect the value of signals and the likelihood of an acquisition. In my research, these conditions are defined in terms of the interaction effects between the inter-organisational relationships of firms and the characteristics of the target firms or the characteristics of the investors or alliances partners associated with potential targets. The next section explores these conditions to enrich understanding about when the value of signals is strongest.

3.4 The Moderating Role of Being a Start-up Firm

Start-up firms can interact with inter-organisational relationships of firms to influence the choice of an acquisition target. Young companies encounter many obstacles that can arise from internal and external constraints which makes it difficult for the acquirer to identify their quality. New organisations often lack a clarification of the roles and structures, the ability to attract qualified employees, and working relationships with customers and suppliers (Aldrich and Auster, 1986; Stinchcombe, 1965). They are less profitable and inefficient in conducting their operations due to little operating experience (Baum and Silverman, 2004). New firms have less information, history and lack a track record of their operations to disclose to acquirers which suggests that the extent and quality of information available on a firm has a clear association with age (Capron and Shen, 2007; Shen and Reuer, 2005).

In addition, new technology start-ups need access to finance to fund their early stage projects and product inventions, which lowers expectations of future revenues (Baum and Silverman, 2004). There is uncertainty associated with the value of a young firm's resources as many of their products are still under development and they may not have patents for all their inventions either (Graebner, Eisenhardt and Roundy, 2010). Moreover, young start-ups do not disclose their inventions due to a risk of imitation (Dushnitsky and Shaver, 2009). Legitimacy is another problem for new firms, especially when certification or licensing is a prerequisite to conducting business (Aldrich and Auster, 1986).

Prior research suggests that the quality of start-ups can be assessed on their ability to go public, securing funding from corporate venture capitalists and involvement in inter-firm relationships such as alliances (Nicholson, Danzon and McCullough, 2005; Dushnistky and Shaver, 2009). Additionally, corporate venture capital investments in young firms provides access to innovative partners and increases innovation potential (Graebner et al., 2010). Previous research has examined how the valuation difficulties associated with the acquisition of young companies tend to be lower for public targets because information disclosure regulations and observable stock prices help buyers calibrate their bids (Capron and Shen, 2007; Shen and Reuer, 2005). Moreover, research frequently addresses the IPO process as a signalling mechanism to differentiate high quality targets from low quality targets (Reuer et al., 2012). Start-up firms can be assessed on the basis of secondary indicators such as their inter-organisational relationships which are third-party endorsements (Stuart et al., 1999). In contrast, firms are less likely to be acquired at an early age if they have access to finance and capital resources through venture capital funding as firms have finance to grow without being acquired (Ransbotham and Mitra, 2010).

When measures of performance do not exist, or cannot be observed, a firm's engagement in inter-organisational relationships function as a certification of future promise and signal quality of firms (Mazzola et al., 2016). In case of uncertainty about the potential of young firms, its inter-organisational relationships can be viewed as a signalling mechanism that distinguishes high quality firms from low quality firms (Hagedoorn and Duysters, 2002). Thus, start-up firms backed by CVC investments and engaged in alliances signal firm quality, reduce information asymmetry and increase its likelihood of being acquired.

Hypothesis 2a: The effect of receiving CVC investments on the likelihood of being acquired is stronger for start-up firms.

Hypothesis 2b: The effect of engaging in alliances on the likelihood of being acquired is stronger for start-up firms.

3.5 The Moderating Role of Reputation of Partners Affiliated with Firms

The reputation of CVC investors and alliance partners affiliated with a firm interacts with the inter-organisational relationships of firms to influence acquisition likelihood. The presence of prestigious partners affiliated with a firm provides 'endorsements' (Stuart et al., 1999) and certify quality of firms (Pollock and Gulati, 2007). The certification mitigates uncertainty associated with cost of assessing a particular firm (Ozmel, Robinson and Stuart, 2013). In addition, CVC investors are more adept at gathering information from other market participants before committing to investing in a particular firm; are selective about the firms they invest in and do evaluations over time (Amit et al., 1998). Follow-on investments in stages allows investors to exchange information about the quality of each firm they invest in and assess the progress and prospects of a firm (Reuer, Tong and Wu, 2012).

Corporate venture capitalists also have longer relationships with firms they invest in, carry out numerous rounds of due diligence and their expertise in different industries adds credence to their investment decisions (Reuer, Tong and Wu, 2012). Affiliations with high reputation partners are costly to imitate (Ozmel et al., 2013) and reflects the extent to which a firm's resources are in demand by other organisations (Katila et al., 2008). A symbolic nature of affiliations with prominent organisations is that they can inspire confidence about firm quality and affect the perceived legitimacy of firms (Higgins and Gulati, 2003). A firm's ability to garner support from organisations with externally validated credentials of worth symbolizes and endorses a firm's strength to attract financial resources (Gulati and Higgins, 2003). Connections with prestigious partners provides access to valuable resources, such as human, social and intellectual capital and cutting-edge ideas that may be important for conducting operations in a firm (Katila et al., 2008).

Relationships with CVC investors take the shape of arm's length ties that involve higher independence from the investor whose main objective is to earn a higher return on investment, and the firm receiving the investment conducts the business functions independently (Dushnitsky, 2012). On the other hand, alliances are close relationships featuring trust, fine-grained information transfer and joint problem-solving between firms (Uzzi, 1996). Although these features are mutually reinforcing, the increasing level of interdependence between firms engaged in alliances with high reputation partners can influence the perceptions of the acquirers and consequently, acquisition likelihood. In such cases, the acquirers may prefer firms backed by CVC investments over firms involved in a greater number of alliances as arm's length ties are featured by lower levels of interdependence. In contrast, affiliations with high reputation investors and increasing number of alliance partners can increase the acquisition premium (Reuer et al., 2012) which in turn can lower acquisition likelihood as acquirers may not always be willing to pay a high price for a potential target. It is worth studying whether the reputation of a firm's partners can influence the decision of an acquirer to takeover a particular firm.

Working alongside a good reputation partner also enhances the future performance of a firm along with signalling its quality (Stuart, 2000). The presence of a well reputed firm or prestigious partner provides further certification purpose to influence acquirers' assessment of the prospects of a firm and affect the value of a firm (Ozmel, Robinson and Stuart, 2013). A firm's connections to high reputation partners "show off" a firm's criteria of worth (Higgins and Gulati, 2003) which makes the firm more favourable in the eyes of the acquirer. This enhances firm quality, improves future prospects of firms and influences it's exit decision (Ozmel, Robinson and Stuart, 2013). I expect that top-tier backing by a CVC investor and affiliations with prestigious alliance partners signal firm quality, decrease information asymmetry, lower the risk of adverse selection and increase likelihood of being acquired.

Hypothesis 3a: The reputation of a CVC investor affiliated with a firm strengthens the effect of receiving CVC investments on the likelihood of being acquired.

Hypothesis 3b: The reputation of an alliance partner affiliated with a firm strengthens the effect of engaging in alliances on the likelihood of being acquired.

CHAPTER 4

Post-Acquisition Innovation Output of Acquired Firms

4.1 The Effect of Acquisitions on Innovation Output of the Target Firm

The extant literature on acquisitions and post-acquisition innovation output gives a number of interesting insights. The arguments in favour of an increase in innovation performance suggest that after an acquisition, an acquired firm increases its innovation output as a result of the exploitation of new R&D scale and scope economies through redeploying resources efficiently between the target and acquirer (Calderini et al., 2003). Economies of scale are achieved by spreading the fixed costs of a business, such as R&D, manufacturing, logistics and sales networks over a higher total volume, whereas, economies of scope occur by cutting costs and sharing assets and resources in an acquisition (Capron, 1999). By eliminating redundant activities, increasing efficiency of operations, and resource reconfiguration firms are likely to generate potential synergies from an acquisition (Capron and Mitchell, 1998; Chondrakis, 2016). Takeover targets can also advantage from an acquisition in the sense that their technologies are successful, provide a cultural fit for the acquired firm and maintain some level of autonomy from the acquiring firm (Graebner, 2004; Zaheer et al., 2013; Graebner and Eisenhardt, 2004).

However, the counter arguments suggest that an acquisition may be seen as a potential risk to the performance of a target firm. The literature points out three main reasons for this. Firstly, innovation activity can reduce in an acquired firm because the manager's commitment is diverted from the innovation strategies to the management of the acquisition process (Cassiman and Colombo, 2006). This decreases the incentive to innovate which can lead the managers or inventors of acquired firms to lose their share on profits from innovative strategies (Seru, 2014). Secondly, a takeover can change the financial leverage of R&D projects being undertaken in an acquired firm, result in the termination of some R&D projects or change the composition of the portfolio of R&D projects (Calderini et al., 2003). Reduced investments in R&D projects that require considerable investments can substantially lower innovation output of acquired firms (Cassiman and Colombo, 2006). Thirdly, an acquisition can also disrupt the organisational routines of a target firm (Paruchuri et al., 2006) and reduce the innovative capacity which may lead to diseconomies of scale and scope (Kapoor and Lim, 2007). A poor management of the post-acquisition process and reduced incentives to innovate can cause the key inventors with high patenting activity to leave the acquired firm which can decrease R&D productivity (Kapoor and Lim, 2007; Seru, 2014; Paruchuri et al., 2006). Thus, acquisitions can have a negative impact on the innovation output of acquired firms.

A key feature of high technology acquisitions is that acquirers seek to create value or synergies by combining together two firms which were otherwise operating independently (Seth, 1990). The difficulty arises in identifying firms that can be combined together to create value following an acquisition. Incomplete knowledge about where valuable information resides in firms can lead acquirers to select an inappropriate acquisition target and affect acquisition outcomes (Meschi et al., 2017; Rogan and Sorenson, 2014; Zaheer et al., 2013; Bena and Li, 2014; Seru, 2014; Chondrakis, 2016).

Drawing on the signalling mechanism, I propose that acquirers rely on information conveyed by the inter-organisational relationships of firms that address the problem of information asymmetry and adverse selection in high technology acquisitions. A firm with inter-organisational relationships, such as, corporate venture capital investments and alliances, reduces information asymmetries between buyers and sellers and signals quality of a firm (Akerlof, 1970; Spence, 1973; Mazzola et al., 2016). In addition, studies have shown that inter-organisational relationships increase firm innovation (Stuart, 2000; Ahuja, 2000). However, little is known in the literature about whether acquired firms with signals exhibit superior innovation performance compared to those that lacked such signals. The following section develops the theoretical background and hypotheses of the study which are grounded in the signalling theory to explore the effect of inter-organisational relationships on post-acquisition innovation output of acquired firms.

4.2 Inter-organisational Relationships and Post-Acquisition Innovation Output

The number of direct inter-organisational relationships a firm has maintained can impact its innovation output positively by providing three advantages: knowledge sharing, complementarity and scale economies (Ahuja, 2000). Knowledge sharing activities allow each firm to receive and exchange higher amount of knowledge from the other than it would otherwise be possible to generate from independent investments (Zaheer et al., 2010; Porrini, 2004). Firms with CVC investments and alliances are an important source of technological knowledge for firms as these boundary spanning ties (Wadhwa, Phelps and Kotha, 2016; Dushnitsky and Lenox, 2005b; Baum et al., 2000; Dushnitsky and Lavie, 2010; Park and Steensma, 2011) allow acquired firms to absorb and use additional knowledge to pursue novel technologies (Graebner et al., 2010). Inter-organisational ties of firms also provide access to complementary skills from different firms (Ahuja, 2000). Firms connected by CVC investments and alliances have developed multiple broad competencies, internal innovation strategy and partnering qualities (Gulati et al., 2008; Galloway et al., 2017; Dushnitsky and Lenox, 2006; Baum and Silverman, 2004) which enables acquired firms with partnerships to enhance their knowledge base and increase innovation potential. As the number of inter-organisational relationships of firms increase, the innovation output of firms increases. For instance, increasing number of CVC investments leads to increasing returns and such investment will lead to a more than proportionate return with regards to innovation output (Engel and Kielbach, 2007; Lerner et al., 2011; Stuart et al., 1999). Similarly, the higher the number of alliances a firm has, the higher the number of patents it produces (Stuart, 2000; Nicholson et al., 2005; Danzon et al., 2005; Danzon et al., 2007).

Inter-organisational relationships of acquired firms influence acquisition outcomes through the mechanisms outlined above. Firms engaged in inter-firm relationships provide information advantage to the acquirers compared to firms that are not connected to other firms in a network (Mazzola et al. 2016; Meschi et al., 2017; Rogan and Sorenson, 2014) which resolves the problem of information asymmetry and adverse selection risk (Akerlof, 1970) in acquisitions. Research shows that firms linked in inter-firm ties increase visibility and eases search for potential partners (Rosenkopf and Almeida, 2003; Schildt and Laamanen, 2006). Firms involved in inter-organisational relationships increase innovation growth (Stuart, 2000; Wadhwa et al., 2016) which is an important facet of acquisitions in the high technology industry. However, the literature on acquisition of firms involved in pre-acquisition inter-organisational relationships lacks a clear understanding on performance of such firms. In this research, I attempt to add to the existing knowledge about the influence of engaging in pre-acquisition inter-firm ties on the post-acquisition innovation outcomes.

The impact of inter-organisational relationships of firms can be explained with the help of three complementary mechanisms. According to the signalling theory, information about the quality of a product is determined by the characteristics of a product that are costly and difficult to imitate (Spence, 1973, 2002). Applying this reasoning to acquisitions of firms, inter-organisational relationships carry information about quality of firms (Stuart et al., 1999; Stuart, 2000) that are costly and difficult to imitate and can significantly affect perceptions of acquirers. In the existence of information asymmetries between buyers and sellers (Akerlof, 1970), insufficient information on potential firms introduces difficulty to discern the quality of firms and its future prospects. The differences in availability of information on firms creates inefficiencies in M&A as sellers can misrepresent their actual value and the buyers may end up purchasing a firm of poor quality, also known as the 'lemons problem' (Akerlof, 1970). A key issue is then to materialise gains from an acquisition. In order to differentiate between high quality and low quality targets, acquirers observe the information available through signals as they provide valuable information about quality of firms (Spence, 1973, 2002). These signals are characteristics of firms that are costly and difficult to imitate and enable buyers to distinguish between high quality and low quality firms (Connelly et al., 2011; Bergh et al., 2014). Therefore, selecting an acquisition target by following signals is likely to affect outcomes of an acquisition as well.

Inter-organisational relationships function as a certification of future promise and signal quality of firms (Mazzola et al., 2016) which aids acquirers to gain clarity on the perception about the quality of prospective target firms. Pre-acquisition inter-organisational relationships lower information asymmetry and limit adverse selection (Mazzola et al., 2016; Meschi et al., 2017; Arend, 2004). The signals allow acquirers to collect fine-grained information at a lower cost and evaluate a potential target firm with less risk (Balakrishnan and Koza, 1993; Hagedoorn and Sadowski, 1999). Prior research also suggests the role of inter-firm relationships as a 'real option' (Van de Vrande and Vanhaverbeke, 2013) to identify potential acquisition opportunities and as a screening mechanism when the target and acquirers have prior relationships between them (Zaheer et al., 2010; Al-Laham et al., 2010). This can reduce moral hazard associated with acquisitions and the risk of adverse selection simultaneously (Arend, 2004).

Secondly, firms engaged in many inter-organisational partnerships are likely to develop absorptive capacity through partner-specific knowledge and learning capabilities (Cohen and Levinthal, 1990), cultivate joint problem-solving abilities and transfer fine-grained knowledge (Uzzi, 1996). Firms involved in inter-firm ties develop coordination routines (Castaner and Oliveira, 2020; Zollo, Reuer and Singh, 2002; Anand and Khanna, 2000; Agarwal et al., 2012). As acquired firms have developed the capacity to collaborate with partners, they may be better positioned to cooperate, adapt and coordinate with the acquirer. Consequently, acquired firms are likely to positively influence post-acquisition innovation performance.

Thirdly, inter-organisational ties can access resources that are unique, valuable, and imperfectly imitable (Barney, 1991) which allow firms to gain an informational and competitive advantage over firms not engaged in partnerships. For instance, research has considered resources accessed through alliance networks to achieve competitive advantage and generation of revenues (Lavie, 2007). Another research investigates the role of alliances to access complementary resources to produce value for firms (Wassmer and Dussauge, 2011). Applying this reasoning, firms with inter-firm partnerships can create value through operational synergies of their connections (Ozcan and Eisenhardt, 2009) and acquired firms engaged in inter-organisational relationships can subsequently lead to an increase in innovation output.

An increasing number of inter-organisational relationships of acquired firms also signals its openness to innovation through external partners like corporate venture capitalists and alliance partners. Innovation combines existing and new knowledge residing inside and outside the boundaries of a focal firm and openness through inter-organisational interactions creates competitive and informational advantages for firms (Laursen et al., 2012). Such inter-organisational relationships can subsequently facilitate boundary spanning searches which are viewed as important for successful innovation (Rosenkopf and Nerkar, 2001). Additionally, acquired firms will have an incentive to innovate (Seru, 2014) as inventors and managers closer to the R&D processes embark on new projects with firms involved in collaborations. Thus, acquired firms with inter-organisational ties are likely to increase innovation performance through mechanisms mentioned above. This leads to the following hypothesis:

Hypothesis 4a: The effect of an acquisition on post-acquisition innovation output is positively related to the number of pre-acquisition CVC investments in a target firm.

Hypothesis 4b: The effect of an acquisition on post-acquisition innovation output is positively related to the number of pre-acquisition alliances in a target firm.

CHAPTER 5

Post-Acquisition Innovation Output of Merged Firms

5.1 Introduction

Post-acquisition innovation performance is one of the most widely researched areas in the M&A literature (Ahuja and Katila, 2001; Cloodt et al., 2006; Bena and Li, 2014; Seru, 2014; Chonrakis, 2016). The key question in this study is to investigate whether the inter-organisational relationships of the targets have an impact on the post-acquisition innovation output of combined (acquiring and acquired) firms. Firms involved in M&A face the problem of information asymmetry which stems from differences in information between acquirers and targets about the quality of firms (Akerlof, 1970). Acquirers tend to rely on the information conveyed by the inter-organisational relationships of the targets as it addresses the problem of information asymmetry and adverse selection in technology acquisitions. Firms engaged in inter-organisational relationships provide informational advantages as it signals quality of firms relative to firms not involved in such relationships. When information on quality of firms is not discernible, the pre-acquisition inter-organisational relationships of firms serve as a signalling mechanism that influence the perception of acquirers and consequently the success of an acquisition. Prior studies do not address the signalling value of pre-acquisition inter-organisational relationships on post-acquisition innovation performance. I aim to address this gap in the literature by examining the effect of inter-organisational relationships of targets on the merged (acquiring and acquired) firm's innovation performance and whether such transactions materialise synergies post-acquisition.

This chapter explains the relationship between inter-organisational relationships of firms and post-acquisition innovation performance and develops the hypotheses of the study.

5.2 The Influence of Pre-acquisition Inter-organisational Relationships of Acquired Firms on the Innovation Output of Merged (Acquiring and Acquired) Firms

In the presence of substantial information asymmetry, it is difficult to evaluate the true value and prospects of a potential acquisition target. Pre-acquisition inter-organisational relationships of the targets, such as, alliances and CVC investments increase the observability and act as credible signals of firm quality of potential acquisition targets. Prior inter-organisational relationships of targets allow acquirers to identify better quality acquisition targets, develop strategies and routines to better integrate the targets (Al-Laham et al., 2010) and can have positive outcomes. The information gathered from inter-organisational relationships facilitates due diligence and triggers subsequent acquisitions (Arend, 2004). Enhanced information available through target relationships can help the acquirer better design and implement the target integration process and achieve synergies.

The signalling perspective brings closer attention towards a new take on the strategy to identify potential takeover targets and overcomes the problem of information asymmetry and adverse selection. Prior research suggests that selecting targets with whom acquirers have prior relationships or share common connections with leads to a biased view of targets (Zaheer et al., 2010; Al-Laham et al., 2010; Rogan and Sorenson, 2014). For example, research indicates that pre-acquisition inter-organisational relationships between acquirer and target may introduce bias into the buyer's beliefs about the quality of a potential target. In the early stages of alliance formation when the two partners are learning about each other, they might ignore the negative outcomes due to the prior favourable beliefs about the target which can lead to inappropriate decisions on the part of the buyer (Meschi et al., 2017). Therefore, some time would have elapsed before the outcomes of an exchange are realized. During this period, the relationship is not affected by any negative aspects and positive information is overestimated. However, the process of learning during this period is positively biased and acquisition decisions made during this time are more likely to have negative outcomes (Meschi et al., 2017).

In addition, common connections among acquirers and target firms might restrict the acquirer's choice to homogeneous partners which reduces the scope for recombination to develop breakthrough inventions and competing products (Rogan and Sorenson, 2014; Capron, Dussauge and Mitchell, 1998). Although common connections between acquirers and targets exposes each other to potential partners, acquirers can also form biased opinion about targets and which can cause negligence in due diligence process (Rogan and Sorenson, 2014). Acquirers might spend less time and effort evaluating the strengths and weaknesses of target firms (Rogan and Sorenson, 2014). Although these studies are important contributions to the literature, these studies highlight important gaps in the literature as well. This literature on pre-acquisition inter-organisational relationships between acquirer and target does not eliminate bias due to selection and its subsequent negative impact on post-acquisition performance. Therefore, it is important to gain clearer understanding of this issue and study the influence of inter-organisational relationships of targets, in general. Such target-specific information helps acquirers to identify better quality targets with valuable information, to separate desirable targets from less desirable ones, increases efficiency of search strategy, creates synergies in the process of acquisition and positively affect post-acquisition innovation performance.

Building on signalling theory, target inter-organisational relationships can be regarded as signals that enable acquirers to differentiate between good quality and poor quality targets (Spence, 1973, 2002). Firms involved in inter-organisational relationships increase visibility of prospective targets (Mazzola et al., 2016), overcome information asymmetry and limit adverse selection problems. As acquirers spend more time observing information on signals of firm quality carried by CVC investments and alliances of prospective target firms, they can make better and more informed decisions about acquiring a potential target and contribute to achieve positive acquisition outcomes. The availability of information through targets relationships can allow acquiring firms to develop plans for coordinating activities (Graebner, 2004) and integrating (Zollo and Singh, 2004) the newly acquired firms and its relationships. The acquirers can take advantage of the information provided by the inter-organisational relationships of the targets to design effective strategies to combine their existing resources with the acquired firms' resources to generate new value through novel ways (Wiklund and Shepherd, 2009). This in turn can have synergistic effects as innovation is realized faster and new technologies can be developed quicker than it would otherwise have been possible. Therefore, pre-acquisition inter-organisational relationships are expected to assist an acquirer in the selection, evaluation and consolidation of a target firm effectively. As a result, this leads to more successful post-acquisition innovation outcomes.

Hypothesis 5a: The effect of an acquisition on post-acquisition innovation output of merged firms is positively related to the number of pre-acquisition CVC investments in an acquired firm.

Hypothesis 5b: The effect of an acquisition on post-acquisition innovation output of merged firms is positively related to the number of pre-acquisition alliances of an acquired firm.

The acquisition outcome will be affected by the extent to which the acquiring firm will be able to manage an expanded network. It can be extremely time consuming to manage such a broad network and diverts the management attention away from innovation and towards devoting effort in managing and maintaining the extended network. Additionally, it will be difficult for firms to differentiate between networks that are going to be used from the networks that need to be retained. The outcome of an acquisition also depends on the degree to which acquiring firms develop specific capabilities to manage the acquisition process (Zollo and Singh, 2004). The transfer of technologies and capabilities will take time and can be complex if the acquirer and acquired firm do not share a common strategy, structure, history or culture (Ranft and Lord, 2002). Acquirers will need to invest more time and deliberate effort to develop their internal competence in managing the acquired firms and the acquired inter-organisational relationships. Therefore, the learning process in the post-acquisition stage affects performance in acquisitions.

According to a study by Seru (2014), shifting some of the R&D activity outside the firm boundary by engaging in alliances and joint ventures after an acquisition explains the decline in R&D productivity. Acquirers engage in alliances to undertake risky ventures in high-tech industries which reduces incentives to innovate (measured by patent count and citations per patent) after an acquisition (Seru, 2014). Alternatively, M&A can be difficult to manage as the acquirers' network expands by taking over targets with inter-organisational partnerships. An acquirer may acquire more knowledge than it can use in a meaningful way (de Man and Duysters, 2005) and this can have negative influence on innovation performance as it increases the cost of incorporating the new knowledge (Katila and Ahuja, 2002). Moving too quickly, without understanding the knowledge-based resources of the targets can be damaging for the acquirer (Ranft and Lord, 2002) and it can take a longer period of time to materialise positive outcomes from an acquisition. Therefore, the following can be expected:

Hypothesis 6a: The effect of an acquisition on post-acquisition innovation output of merged firms is negatively related to the number of pre-acquisition CVC investments in an acquired firm.

Hypothesis 6b: The effect of an acquisition on post-acquisition innovation output of merged firms is negatively related to the number of pre-acquisition alliances of an acquired firm.

CHAPTER 6

METHODOLOGY

6.1 Introduction

In this chapter, I provide detailed information on the econometric approach applied to test the hypotheses, sources of data collection, construction of the sample and operationalisation of variables. I constructed an original dataset for my dissertation by combining information from seven separate databases. This was an important process to test the hypotheses which comprised of a complex set of characteristics of firms influencing choice of acquirers and the associated acquisition innovation performance outcomes for the acquired and merging firms. The dataset includes information at the firm level on acquisitions (Thomson One), CVC investments (Thomson One Private Equity), alliances (SDC Platinum), patents and citations (OECD Patent and Citations databases), financial and accounting indicators (FAME), corporate family (Hoover's Online) and business news magazines (Fortune and Forbes).

The first study involves choice of a potential target through a comparison of the characteristics of acquired and non-acquired firms engaged in inter-organisational relationships. In order to address this, the empirical strategy is to first match the characteristics of acquired and non-acquired firms using coarsened exact matching. The selection of a target firm is modelled through a logit regression. The second study analyses the effect of an acquisition (considered as a treatment variable) on the innovation performance of acquired firms through a difference-in-differences analysis. As the study looks at the effect of an acquisition on the innovation performance of acquired firms in relation to their inter-organisational relationships, a triple differences analysis is applied to account for this. In the third study, the unit of analysis is the combined firm, that is, the acquired and acquiring firms. To evaluate the effect of an acquisition (considered as a treatment variable) on the innovation output of merged (acquired and acquiring) firms, a difference-in-differences approach is applied. As the research is interested in examining the effect of an acquisition on the innovation output of merged (acquired and acquiring) firms as a function of the inter-organisational relationships of the targets, a triple differences approach has been adopted. The empirical strategy is implemented with coarsened exact matching method on acquiring firm characteristics to account for selection bias.

The following sections describe the econometric model applied, sources of data collection, sample construction, variables and measures employed in all the three studies completed as part of the dissertation.

6.2 Econometric Model

6.2.1 Study 1: Target Firm Selection Model

The aim of the first study is to examine the influence of inter-organisational relationships of firms on the likelihood of being acquired and to explore the boundary conditions affecting the probability of selecting an acquisition target. Inter-organisational relationships, in terms of CVC investments and alliances, have been viewed as a due diligence strategy and sources of information-gathering that help mitigate information asymmetry and adverse selection risk. These work as signals to separate high quality firms from low quality firms and affect acquisition likelihood. Such relationships can also interact with different conditions to influence target selection. Therefore, I investigate whether firms engaged in inter-organisational relationships, that is, CVC investments and/or alliances, affect acquisition likelihood (Hypothesis 1a and 1b). I then look at the moderating effects: of being a start-up (Hypothesis 2a and 2b) and the reputation of a CVC investor (Hypothesis 3a) and alliance partner affiliated with a firm (Hypothesis 3b).

To model the selection of an acquisition target, a discrete choice model will be applied. This predicts choice between two or more discrete alternatives (Wooldridge, 2009). For example, these have been applied in prior M&A studies to predict takeover targets (Desyllas and Hughes, 2009). A discrete choice model statistically relates the choice made by each individual or organisation to the characteristics of the individual or organisation and the characteristics of the alternatives available to the individual or organisation (Wooldridge, 2009). The choice set is complicated by the fact that an acquiring firm's selection can be influenced by a variety of characteristics of the potential target firm, such as, profitability, firm size, age, financial assets and innovation aspects. To estimate the choice of a target firm, the study follows the matching methodology approach used by Rogan and Sorenson (2014). First, each acquired firm is paired with observably equivalent targets that could have been acquired through coarsened exact matching (CEM). In the target firm selection model, the treated unit is the acquired firm and the non-treated units are the non-acquired (control) firms. The aim of matching is for every treated unit, to find one or more non-treated units with similar observable characteristics (Hamilton and Nickerson, 2003). This enables a comparison of outcomes among treated and non-treated units and controls for potential selection bias (Blackwell et al., 2009). Second, after the matching method, a logit model is applied on the matched data set to estimate the acquisition probability (Gujrati, 2003; Wooldridge, 2009). The logit regression equation is as follows:

$\text{Acquisition}_{i,t} = \alpha + \beta_1$ CVC Investments + β_2 Alliances + β_3 Financial and Accounting Indicators + β_4 Innovation Characteristics + Industry Effects + Year Effects + μ

The equation including the interactions would be as follows:

$\text{Acquisition}_{i,t} = \alpha + \beta_1$ CVC Investments + β_2 Alliances + β_3 Start-up + β_4 (CVC Investments X Start-up) + β_5 (Alliances X Start-up) + β_6 CVC Partner Reputation + β_7 (CVC Investments X CVC Partner Reputation) + β_8 Alliance Partner Reputation + β_9 (Alliances X Alliance

Partner Reputation) + β_{10} Financial and Accounting Indicators + β_{11} Innovation Characteristics + Industry Effects + Year Effects + μ

In the equations above, the dependent variable, Acquisition denotes the firm being acquired (*i*) in a particular year (*t*). The independent variables, inter-organisational relationships considered are CVC investments and alliances of firms. The regression controls for other characteristics of firms such as innovation and financial performance. The interactions are between each type of inter-organisational relationship examined and a firm being a start-up and a firm affiliated with reputable CVC investors and alliance partners. The next sections discuss study 2 (section 6.2.2), study 3 (section 6.2.3), the econometric models (sections 6.2.4, 6.2.5 and 6.2.6) and then describes the matching methods applied (sections 6.2.7 and 6.2.8).

6.2.2 Study 2: Acquired Firm Innovation Performance Model

In the second study, the unit of analysis is the target firm. It studies whether acquired firms with inter-organisational relationships will have an impact on innovation output post-acquisition. The hypothesis 4a, tests whether the acquisitions with pre-acquisition CVC investments in a target firm will have a positive effect on post-acquisition innovation output. The hypothesis 4b, tests whether the acquisitions with pre-acquisition alliances in a target firm will have a positive impact on post-acquisition innovation output. The hypotheses are tested by examining the effects of pre-acquisition inter-organisational relationships on innovation outcomes by using two measures of innovation performance: (i) patent output and (ii) citations output, from three years before an acquisition to three years after an acquisition. The patent output shows the quantity of post-acquisition innovation performance of acquired firms, whereas, citations output explains the quality of post-acquisition innovation output of acquired firms. The operationalisation of variables is discussed in detail in section 6.5. The analysis has been conducted in two steps. The first step is to apply coarsened exact matching method to build a matched sample of acquired firms and non-acquired firms on the observed characteristics of the treated and control groups. The matching method reduces the problem of selection bias in this analysis phase. The second step is to estimate the effect of the treatment on the matched sample. Here, the acquisition has been considered as treatment. The treatment effect is estimated with a difference-in-differences (DID) analyses to estimate the effect of an acquisition on innovation performance of acquired firms. An additional difference is taken called the difference-in-difference-in-differences (DDD) analyses to estimate the effect of an acquisition on innovation output of acquired firms as a function of their inter-organisational relationships. The outcome variables, patent and citations output are both count variables for which a Poisson regression has been employed. More in-depth discussion on the DID, DDD and Poisson methods is provided in sections 6.2.4, 6.2.5 and 6.2.6.

6.2.3 Study 3: Merged Firm's Innovation Performance Model

In the third study, the unit of analysis is the combined firm – that is, the acquired and acquiring firm. It investigates the impact of pre-acquisition inter-organisational relationships of the targets on the post-acquisition innovation output of merged (acquired and acquiring) firms. These predictions are made in hypotheses 5a, 5b, 6a and 6b. The hypotheses examine the effects of an acquisition on the post-merger innovation performance of merged firms as a function of the connected targets. The innovation output of merged pairs is measured as: (i) the combined patents of the acquired and acquiring firms and (ii) the combined citations output of the acquired and acquiring firms. More to follow on this in section 6.5. The empirical strategy is to implement coarsened exact matching method on acquiring firms with triple differences analysis. First, a matched sample is obtained on acquiring firms based on the observed characteristics of the acquiring and control firms. This corrects any biases that could arise due to the presence of selection bias in the sample. The matched sample of potential acquiring firms is combined with the matched sample of potential acquired firms to generate potential deals that could have occurred[3]. Second, the impact of the treatment is evaluated by a DID and DDD research design. Specifically, implementing matching estimators with DDD analyses facilitates causal interpretation of the effect between the outcome of interest and the selected treatment and corrects for selection biases in the sample. The next section looks at the method of estimation implemented in the research.

6.2.4 Difference-in-Differences Estimation

To estimate the effect of an acquisition on innovation performance, the study uses a difference-in-differences research design. The event for which the study is interested in estimating the effect is called the treatment which is acquisition in case of my study. A difference-in-differences (DID) set up is one where outcomes are observed for two groups for two time periods (Imbens and Wooldridge, 2007). One of the groups (treated group) is exposed to a treatment in the second period not in the first period (Imbens and Wooldridge, 2007). The second group (control group) is not exposed to treatment during either period (Imbens and Wooldridge, 2007). In the case where the same units within a group are observed in each time period, the average gain in the second group (control group) is subtracted from the average gain in the first group (treatment group) (Wooldridge, 2002). This removes the biases in the second period comparisons between the treatment and the control group that could be the result from permanent differences between those groups, as well as biases from comparisons over time in the treatment group that could be the result of trends (Wooldridge, 2002).

The outcome denotes the variable that will be used to measure the effect of the treatment. The effect of an acquisition on innovation output post-merger is operationalised by two ways: (1) patent output, and (2) citation output. A detailed description on the operationalisation and measurement of variables has been provided in section 6.5. There are two time periods considered, one denotes pre-acquisition period and the second denotes post-

[3] More details on this are provided in section 6.4.5.

acquisition period. For a DID estimator to be unbiased, it requires the treatment to not be systematically related to other factors that affect the outcome. Outcomes that would be realised if a specific treatment has been applied are called potential outcomes. A variable is called confounding if it is related to the treatment and the potential outcomes. Additional covariates can be added to account for the characteristics of firms in the analysis. A difference-in-differences method is an attractive choice when using research designs based on controlling for confounding variables or using instrumental variables is deemed unsuitable, and when pre-treatment information is available simultaneously (Wooldridge, 2002).

The difference-in-differences estimator is obtained by comparing the mean outcome changes over time between treatment and comparison groups (Ravallion et al., 2005). In the case of my research, treatment means being acquired. The study compares the acquired firms (cases) with similar firms that are not acquired (control sample). The difference-in-differences estimator subtracts the average change in the control sample from the average change in the treatment sample, thereby removing confounds that could result either from trends or from stable differences across the samples receiving and not receiving treatment (Rogan and Sorenson, 2014). The equation for analysing the impact of an acquisition is:

$$y = \beta_0 + \delta_0 \, d2 + \beta_1 \, dB + \delta_1 \, d2 \text{ x } dB + \mu$$

Where,

y is the outcome variable of interest,

d2 is the period dummy which equals one for the second (post-acquisition) time period and captures aggregate factors that affect 'y' over time in the same way for the treated and control groups; dB is a dummy variable which equals one for firms in the treatment group and zero otherwise. It captures possible differences between the treatment and control groups before the acquisition. The coefficient of interest, δ_1, multiplies the interaction term d2 x dB, which is a dummy variable equal to unity for those observations in the treatment group in the post-acquisition period.

The estimation of the treatment effect is based on data averages for the treated and control groups in the two periods (pre-acquisition and post-acquisition) as depicted by the following equation:

$$\delta_1 = (y_{treatment,after} - y_{treatment,before}) - (y_{control,after} - y_{control,before})$$

The estimator δ_1 is called a difference-in-differences estimator of the treatment effect.

The sample means are:

$y_{treatment,after}$ = mean of y for the treatment group after acquisition

$y_{treatment,before}$ = mean of y for the treatment group before acquisition

$y_{control,after}$ = mean of y for the control group after acquisition

$y_{control,before}$ = mean of y for the control group before acquisition

When the treatment has been randomly assigned, the estimated effects can be interpreted as causal. Acquisitions do not occur at random. An additional differencing in the estimator is included to examine the results of the factors correlated with being acquired, known as the difference-in-difference-in-differences approach. The triple differences technique has been used in management and finance studies by Rogan and Sorenson (2014), Bena and Li (2014) and Seru (2014). In my research, a triple differences method estimates the influence of pre-acquisition inter-organisational relationships of acquired firms on post-acquisition innovation performance of acquired (merged) firms[4]. The main idea is to find the

[4] The unit of analysis is the acquired firm in the second study and the merged (acquired and acquiring) firm in the third study.

differential effects of acquisition as a function of inter-organisational relationships of firms, that is, the number of CVC investments and the number of alliances. First, the study estimates the difference-in-differences for acquired firms with a certain number of inter-organisational relationships. This provides information on (a) how the acquired firms with at least one inter-organisational relationships pre-acquisition change post-acquisition relative to firms with at least one inter-organisational relationships that are not acquired; and (b) how the acquired firms without inter-organisational relationships before an acquisition change after an acquisition relative to firms without inter-organisational relationships that are not acquired. Each of these differences provides an estimate of the effect of an acquisition conditional on a particular number of inter-organisational relationships. The triple differences estimator then takes the difference between the differences described in–(a) and (b)–to compute an estimate (Rogan and Sorenson, 2014) of how the effect of an acquisition depends on the number of inter-organisational relationships of firms, that is, the number of CVC investments and the number of alliances. The estimates net out selection in who gets acquired and focus on variation in the effects of acquisition as a function (Rogan and Sorenson, 2014) of inter-organisational relationships, that is, CVC investments and alliances.

The equation for analysing the impact of an acquisition as a function of inter-organisational relationships of firms is as follows:

$$y = \beta_0 + \beta_1\ dB + \beta_2\ dE + \beta_3\ dB \times dE + \delta_0\ d2 + \delta_1\ d2 \times dB + \delta_2\ d2 \times dE + \delta_3\ d2 \times dB \times dE + \mu$$

Where,

y is the outcome variable of interest,

d2 is the period dummy and dB is the dummy denoting the treatment group (as described above for DID), dE denotes inter-organisational relationships (CVC investments and/or alliances) of firms,

The coefficient of interest is δ_3, which is the coefficient on the triple interaction term, d2 x dB x dE.

$$\delta_3 = (y_{B,E,2} - y_{B,E,1}) - (y_{A,E,2} - y_{A,E,1}) - (y_{B,N,2} - y_{B,N,1})$$

where, A denotes control group of firms, B denotes the treatment group, E denotes inter-organisational relationships and N denotes no inter-organisational relationships. In the equation, the numbers 1 and 2 denote the pre-acquisition and post-acquisition time period, respectively. The estimator, δ_3, is called difference-in-difference-in-differences (DDD) estimate. The DDD estimate starts with time changes in averages for firms with inter-organisational relationships in the treatment group of firms and then nets out the change in means for firms with inter-organisational relationships in the control group of firms and the change in means for firms without inter-organisational relationships in the treatment group (Imbens and Wooldridge, 2007).

The identification approach relies on triple differencing. The research estimates whether the firms that are acquired (merged) managed to grow their patent output and citations received per patents faster than the firms that were not acquired (non-merged) and the extent to which that differential depended on whether the firms were engaged in inter-organisational relationships, that is, CVC investments and alliances, prior to being acquired (merged).

A single difference comparisons of outcome measures between acquired and non-acquired firms engaged in inter-organisational relationships can give biased estimates of impact if potential selection is not controlled for. In order to reduce the selection bias, comparisons are often confined to observationally similar ("matched") units. Coarsened exact matching (CEM) method is a means of balancing the covariates between the treated and the control groups (Blackwell, 2010). However, the problem of selection bias remains, that is, there may be latent differences between the two groups in characteristics that jointly influence acquisition and outcomes; selection bias violates the conditional independence assumption underlying CEM (Ravallion et al., 2005). The difference-in-difference-in-differences estimator addresses this problem. However, there is still a bias in DDD estimator when the subsequent outcome changes are a function of initial conditions that also influence firm innovation performance. Thus, it is still important to ensure that the treatment and control groups are similar. Combining coarsened exact matching and difference-in-difference-in-differences can greatly reduce the bias (but not eliminate bias) (Ravallion et al., 2005). The coarsened exact matching method has been explained in detail in section 6.2.8. After pre-processing the data with CEM, a Poisson regression with triple differences analysis is applied to estimate the effect of an acquisition on innovation performance as a function of the inter-organisational relationships of the targets.

6.2.5 Triple Differences Estimation and Poisson Regression

To compute the difference-in-difference-in-differences (DDD) estimate, a three-way interaction is computed and consists of the following variables:

1) A variable called acquired (merged) which takes the value 1 for the treatment group and 0 for the control group,

2) A variable called time which takes the value 1 for the post-acquisition time period and 0 for the pre-acquisition time period; the pre-acquisition and post-acquisition time period used is 3 years before an acquisition and 3 years after an acquisition,

3) The variable, CVC Investments (alliances) which is the number of CVC investments (alliances) in a firm,

4) The interaction between the variables acquired (merged), time and CVC investments (alliances).

The DDD estimate starts with time changes in averages for firms with CVC investments (alliances) in the treatment group and then nets out the change in means for firms with CVC investments (alliances) in the control group and the change in means for firms without CVC investments (alliances) in the treatment group (Imbens and Wooldridge, 2007).

I focused on a three-year time window to measure pre-and post-acquisition innovation performance outcomes similar to practice which have also been used in previous studies on acquisitions and innovation, see for example, Bena and Li (2014); Seru (2014); Rogan and Sorenson (2014); Desyllas and Hughes (2010). An advantage of using a three-year time period is that it provides a reasonable window for the effects of an acquisition to materialise and to evaluate the effects. It also prevents estimation difficulties that may arise due to existence of confounding variables in lengthy estimation time frames and lowers loss of observations in the sample due the unavailability of the data. Lastly, acquisitions that occur towards the end of the sample period can be analysed. A review of the literature indicates that researchers analysing the effect of an acquisition on patenting activity use a minimum of two-year window which is a medium-term effect (Calderini et al., 2003) and a maximum of four-year window which are long-term effects of an acquisition (Ahuja and Katila, 2001; Ornaghi, 2009).

In the acquired firms' innovation performance analyses which is the second study, the approach is to compare the observed patent output and citations received per patent changes of acquired firms with inter-organisational relationships. The acquired firms are matched with non-acquired firms by coarsened exact matching derived from their observed characteristics to account for selection bias. This is followed by an implementation of DID and DDD analysis on the matched data set. The analysis explains the change in quantity and quality of output of the acquired firms in relation to their inter-organisational relationships.

In the merged firms' innovation performance analyses, which is the third study, the acquiring firms are matched with non-acquiring firms using coarsened exact matching to account for acquiring firm characteristics that might be correlated with the outcome. The matched potential acquiring firms are randomly combined with matched potential acquired firms to create counterfactual acquisitions[5] (deals that could have happened). The analysis then depicts changes in patent and citations output of the merged (acquired and acquiring) firms as a function of the inter-organisational relationships of the connected targets.

As the dependent variable is the number of patents and the number of citations received by patents, which represents a count, I estimated the model using a maximum likelihood Poisson regression. Prior studies that have a count variable as a dependent variable also apply a Poisson model. For example, Ahuja and Katila (2001) measure innovation performance by the number of patent applications granted to a firm and employ a Poisson regression analysis as their dependent variable is also a count variable. The data display overdispersion, as the variance is greater than the mean. The Poisson regression make the assumption that whether or not the distributional assumptions are met, the estimates of β will be consistent and asymptotically normal (Wooldridge, 2002).

6.2.6 Interpreting Three-way Interaction

The three-way interaction includes all the first-order and second-order terms (Aiken and West, 1996). In the case of my research, the three-way interaction includes two dummy variables and one continuous variable. The continuous variable is centered on the mean to maximise the interpretability and to minimise the problem of multicollinearity (Aiken and West, 1996). The continuous predictor variable has been put in deviation score form so that their means are zero (Aiken and West, 1996). The predictor for the three-way interaction is formed by multiplying together the three predictors, e.g., *Acquired X Time X CVC Investments*.

[5] A detailed description on the construction of the combinations between potential acquirers and potential targets is provided in the sample construction section 6.4.5.

The coefficient on the triple interaction term indicates whether a three-way interaction is significant. The three-way interactions *Acquired X Time X CVC Investments* represent conditional interaction effects, evaluated when the third variable (that is, inter-organisational relationships – in this example CVC investments) is centred at its mean. With centered predictor variables, the three-way interaction is interpreted as conditional interaction effects at the mean of the variable in the interaction (Aiken and West, 1996).

6.2.7 Matching methods

Prior to applying a statistical model for estimation, it is useful to replicate a randomized sample as closely as possible by obtaining groups with similar covariate distribution (Stuart, 2010). To employ matching methods, the treated and control groups should be randomly different from one another on all background covariates[6]. Work on matching methods has examined how to replicate this for observed covariates with observational (nonrandomized) data (Ho et al., 2007). Matching is defined as any method that aims to balance the distribution of covariates in the treated and control groups (Stuart, 2010). The causal inference methods based on observational data make the assumption of no omitted variable bias and condition on the definition of a key causal (or treatment) variable and a set of control variables (Iacus et al., 2012). Using this as a common starting point, the matching methods adjust for the information in the control variables without parametric assumptions (Stuart, 2010). This is done by pre-processing a data set with matching methods so that the treated and control groups are similar. In the pre-processed data set, the treatment variable is closer to being independent of the background covariates, which renders any subsequent parametric adjustment less important (Ho et al., 2007).

[6] In the first study, to estimate the impact of inter-organisational relationships on the likelihood of being acquired, the matching method is employed which ensures that the acquired and control firms are comparable in various respects but their pre-acquisition inter-organisational relationships. In this way, the estimates show the impact of inter-organisational relationships of firms on the likelihood of being acquired. The estimation of the acquisition likelihood is useful in the analyses later when estimating the effect of an acquisition on innovation performance models of Study 2 and 3.

This has a few advantages. First, a pre-processing step is added before the parametric analysis procedure to follow the best practices. Second, by reducing the link between the treatment and control variables, pre-processing makes estimates based on the subsequent parametric analyses less dependent on modelling choices (Ho et al., 2007). Lastly, since most of the adjustment for potentially confounding control variables is done non-parametrically, the potential for bias is greatly reduced compared to parametric analyses based on raw data (Blackwell et al., 2009). The pre-processing also leads to a reduction in the variance of the estimated causal effects, and the mean squared error is lower too (Ho et al., 2007). The following section describes the matching method I have applied in my research.

6.2.8 Coarsened Exact Matching

The main idea of coarsened exact matching (CEM) is to prune observations from the data on each variable into substantively meaningful groups, assign a strata to the matched observations of the treated and control units, and then only retain the original values of the matched data (Iacus et al., 2012; Blackwell et al., 2009). I used CEM to estimate unobserved potential outcomes by comparing treated and control groups that are as similar as possible to each other. In CEM, the covariates used to match the treated and control groups can be chosen by ex-ante user and can either chose to do an exact match on each variable or match on user-defined cut-points (Iacus et al., 2011). This feature is not common in other matching methods. CEM algorithm performs exact matching on coarsened data to determine matches and then passes on the uncoarsened data from observations that were matched to estimate the causal effect (Blackwell et al., 2010).

Exact matching works by first sorting all the observations into strata, each of which has identical values for all the coarsened pre-treatment covariates, and then discarding all observations within any stratum that does not have at least one observation for each unique value of the treatment variable (Blackwell et al., 2009). CEM prunes observations that have no close matches on pre-treatment covariates in both the treated and control groups (Blackwell et al., 2010). The result is less model-dependence, lower bias and by removing heterogeneity there is increased efficiency (Iacus et al., 2012). The method also assures that adjusting the imbalance on one variable has no effect on the maximum imbalance of any other (Iacus et al., 2009). Besides bounding the imbalance between the treated and control groups, CEM is computationally efficient even for large data sets (Iacus et al., 2011).

The present study is based on observational data and acquisitions of firms are not random. In order to take into account, the systematic differences between characteristics of acquired and non-acquired firms, the study uses a matching method to replicate randomized samples as closely as possible to balance the treated and control groups (Stuart, 2010). Matching methods in statistics selects and compares firms in the treatment and control group with similar covariate distribution (Stuart, 2010). The method comprises pruning observations from the data so that the remaining data have better balance between the treated and the control groups, which means that the empirical distributions of the covariates in the groups are more similar (Blackwell et al., 2009).

The choice of covariates used for coarsening depends on the variables known to be related to the outcome[7] (Stuart, 2010). In my study, the covariates used in matching are firm size (measured by the natural logarithm of number of employees), firm profitability (measured by the return on total assets) and 4-digit industry SIC codes. The CEM procedure selects firms at random without replacement that matched the acquired firms on firm size as measured by the natural logarithm of number of employees, firm profitability as measured by the return on assets, 4-digit industry SIC codes, and the year of observation. For the variables used in matching, an exact match is obtained for 4-digit industry SIC codes and year of observation. For firm size and profitability, natural breaks in the data are used to create the coarsening as it

[7] In the first study on the acquisition likelihood model, the outcome denotes acquisition of a firm. In the second study on the acquired firm's innovation performance, the outcome denotes the innovation output of acquired firms post-acquisition. In the third study on the innovation performance of merged firm's model, the outcome denotes the innovation output of merged (acquired and acquiring) firms after an acquisition.

is a better approach than using fixed bin sizes that disregard the meaningful breaks in the data (Blackwell et al., 2009).

The matching algorithm computes the overall imbalance which is given by the L1 statistic (Iacus et al., 2009) and it is based on the difference between the multidimensional histogram of all pre-treatment covariates in the treated group and control group (Blackwell et al., 2009). The L-statistic measures imbalance between 0 to 1 and a perfect global balance is indicated by L1 = 0, with a maximum of L1 = 1, which indicates complete separation. The L1 value is not valuable on its own, but rather as a point of comparison between matching solutions. After the matching solution is obtained, its L1 value will be compared to the original imbalance to check the increase in the balance due to the matching solution from that difference[8]. A good matching solution would produce a reduction in the L1 statistic (Blackwell et al., 2010), that is, one would hope to have L1 (before matching) < L1 (after matching).

After matching on the pre-treatment variables, that is, size, profitability, 4-digit industry SIC codes, and year of observation, the output gives the number of observations in total, matched, and unmatched by treatment group and gives information about the quality of the matched data (Blackwell et al., 2009). The L1 statistic is also shown after matching. By comparing the imbalance results to the original imbalance, it can be seen that a good match can produce a substantial reduction in imbalance in the distribution of the data. CEM also generates weights for use in the evaluation of imbalance measures and estimates of the causal effect.

The analysis is done on the matched data and weights are incorporated into the analyses for variable ratio matching, where the control group members receive a weight that is proportional to the number of controls matched to the treated individual (Ho et al., 2007; Stuart,

[8] Please note that Blackwell et al. (2010) document that the imbalance statistic (L1) is indicated by a higher imbalance before matching and a reduction in the imbalance after applying the matching algorithm. In their example, the value of L1 = 0.51 before matching which reduces to L1 = 0.46 after matching. A good match produces a substantial reduction in imbalance of the data. Therefore, this means that L1 before matching should be less than L1 after matching.

2010). For example, if 1 treated individual was matched to 3 controls, each of those controls receives a weight of 1/3. If another treated individual was matched to just 1 control, that control receives a weight of 1. After pre-processing the data with CEM, any regression analysis or statistical model can be applied on the matched dataset.

6.3 Sources of Data

The study creates an original dataset by gathering information on mergers and acquisitions, CVC investments, alliances, financial and accounting information, patents and citations, and reputation indicators in media news magazines. The online databases used include Thomson One, Thomson One Private Equity, SDC Platinum, FAME, OECD Patent and Citations databases, and business news of firms is collected from magazines such as Fortune magazine's World's Most Admired Companies and Midas List published by Forbes. These are listed in table 6.1. below. A detailed description of the databases and data items is given in the following subsections.

Table 6.1. Data items and sources of information.

Data Item	Sources
M&A	Thomson One
CVC Investments	Thomson One Private Equity
Alliances	SDC Platinum
Financial and Accounting Data	FAME
Patents	OECD Patent Database
Citations	OECD Citations Database
Corporate Family	Hoover's Online
Reputation Indicators	World's Most Admired Companies published by Fortune magazine; Midas list published by Forbes magazine.

6.3.1 FAME

FAME is an online database maintained by Bureau van Dijk. It provides extensive coverage of data on financial ratios, equity and capital market data, interest and exchange rate data, economic and industrial statistics for current and historical companies, company structures and the corporate family on public and private firms. It covers information on over 11 million companies in the UK and Ireland, which include details of 1.3 million companies that are active and 6 million companies that are no longer active. It also gives information on name changes of firms, dates of name change, and has identifiers such as, company names, BVD ID and registered number. These identifiers are also present in Hoover's Online and proved useful to track information on ownership changes, names of corporate parents and subsidiaries of firms. The database was used to gather information on the population of firms comprising the sample of targets and acquirers in a broad range of industry sectors in UK.

6.3.2 Thomson One

The study gathers data on mergers and acquisitions from Thomson One which is an online database provided by Thomson Reuters. It is one of the most comprehensive databases of company information and business intelligence. It provides information on private equity, investment banking and M&A deals, covering data on more than 55,000 public company overviews and one million private global companies since 1985.

An acquisition is defined as a deal where the acquiring firm increases its ownership and acquires at least 50% of target firm's shares as a result of the takeover (Desyllas and Hughes, 2009). This database was used to collect information during the period 2008 – 2016, to create two samples on: (1) acquisitions of public and private high technology firms in the UK by worldwide public companies in all industry sectors, and (2) domestic acquisitions of public and private high technology firms by public acquirers in the high technology and non-high[9] technology sectors in the UK. These selection criteria are listed in the tables 6.2. and 6.3 below. The database includes identifiers such as CUSIP and company names. The information on

[9] The sample of domestic UK acquisitions shows non-high technology acquirers in SIC 15 Building Construction, SIC 17 Construction, SIC 34 Fabricated Metal Products (except machinery and transportation equipment), SIC 39 Miscellaneous Manufacturing Industries, SIC 50 Wholesale Trade (Durable Goods), SIC 60 Depository Institutions, SIC 61 Non-Depository Credit Institutions, SIC 62 Security and Commodity Brokers, Dealers, Exchanges and Services, SIC 63 Insurance Carriers, SIC 64 Insurance Agents, Brokers, and Service, SIC 67 Holding and Other Investment Offices, SIC 72 Personal Services and SIC 80 Health Services. A complete list of acquirers' 2-digit industry SIC codes is attached in the Appendix A.

acquisitions is matched with the population of firms from FAME using company names as an identifier.

Table 6.2. Target and acquiring firm specificities in Study 1 and 2.

Sample of Mergers and Acquisitions	
Time period	2008 – 2016
Target Nation	UK
Target Industry	High Technology
Target Status	Public and Private
Acquirer Nation	All Nations
Acquirer Industry	All Industry Sectors
Acquirer Status	Public

Table 6.3. Acquiring and target firm specificities in Study 3.

Sample of Mergers and Acquisitions	
Time period	2008 – 2016
Acquirer Nation	UK
Acquirer Industry	High Technology & Non-High Technology
Acquirer Status	Public
Target Nation	UK
Target Industry	High Technology
Target Status	Public and Private

6.3.3 Thomson One Private Equity

The study collects data on CVC investments from Thomson One Private Equity section of the Thomson One database. This is an online database provided by Thomson Reuters. It was previously known as the Thomson VentureXpert database and has been used in the study by Vrande and Vanhaverbeke (2013) to extract CVC data. This database provides a comprehensive coverage of data on private equity funds, buyouts, firms, portfolio companies, limited partners and invested companies that are and are not publicly traded around the globe.

The database covers information from 1990 onwards, and offers data elements on the number of investments, rounds or stage of investment, date of investment and more. The amount of investment is not always available as a few investments are sometimes less than 1 million USD. It provides complete information on the number of investments that a firm receives which seemed a reasonable method to operationalize the variable on CVC investments. Identifiers such as CUSIP or company names can be used to match information between Thomson One and Thomson One Private Equity. Company names were used to match information between this database and FAME.

6.3.4 SDC Platinum

The data on alliances of firms is collected from Securities Data Company (SDC) Platinum which is an online database provided by Thomson Reuters. It has the most detailed financial transactions information available on alliances, M&A, syndicated loans, bonds, private equity, project finance and poison pills. It collects data from the US Securities and Exchange Commission (SEC) filings, trade publications, wires, and news sources. It includes information on different types of agreements, such as, joint ventures, alliances, R&D agreements, sales and marketing agreements, manufacturing and supply agreements, and licensing and distribution agreements. It covers agreements between industrial partners, universities and government labs as well. The database provides information from 1990 onwards, and offers data items on SIC codes, nationality of participants, deal terms and deal synopsis for alliance agreements. In some cases, there is missing information on alliance termination dates, as the information is not reported in the database (Schilling, 2009). To address this concern, a window of 3 years is used on the alliance data. According to the research by Schilling (2009), the database covers information on 52,000 research and technology agreements between 1990 – 2005. Company names were used as an identifier to match the information on alliances with the firms from FAME.

6.3.5 OECD Patent Database

Patent data has been collected from the OECD Patent database (2018). This database primarily collects information on patents from PATSTAT which is EPO's Worldwide Statistical Patent Database. It holds information on patent applications filed at the EPO (European Patent Office), JPO (Japan Patent Office) and USPTO (United States Patent and Trademark Office). The database covers information on patents filed by corporate firms or their subsidiaries, universities and government labs and institutions and offers information on more than 3 million patent publications. The data gives information on the names of patenting firms, their unique identifier, patent application number, description of the patent filed, application filing date, and grant date. The database was used during the time period of the analysis. For a firm that applies for a patent to protect the same invention to all the three offices, the patents are counted as a single record. For the purpose of this dissertation, patent data was first matched and linked with the sample of targets from FAME and then with the sample of acquirers retrieved from FAME. The matching of the two datasets by firm name proved to be a challenging, large-scale task, that required a great deal of time and effort in the research. Patents can be granted under a variety of names (corporate parent names or their subsidiaries) and the database used does not keep a unique identifier to track each parent and its subsidiary patenting firm from year to year. I obtained the corporate family structures and their subsidiaries from Hoover's Online. Besides firms filing patents under different names, the matching procedure is compounded by the fact that there were numerous spelling mistakes in the names and some used abbreviations. Due to the large volume of patent data, a program was developed in Python to produce a map linking the patenting firms in the patent database with population of firms from FAME. Python is a computer programming language used by programmers in industry and academia working on various small- and large-scale projects. The program was implemented as follows:

1) Create two separate datasets: one containing the name of firms from FAME and the other containing the name of firms from the patent database. Read in the datasets in the program.
2) A dictionary map is applied to remove suffixes (for example, LLC, Inc. LTD etc.). The program will identify exact matches on firm names between the two datasets and assign a unique ID called 'mapid0' to the datasets.
3) The program identifies inexact matches and exports files and saves them in the relevant directory.

Although doing this increased the efficiency of the work, it was subject to a few errors. A manual search was done to ensure that firms (same firms with different spellings etc.) have been assigned the correct ID. The same procedure is followed to form a link between acquirer's sample and patent databases. The original mapping program description has been attached in Appendix B. The sample consists of EPO patent data because it gives largest coverage for all UK firms. Also, it is essential to maintain consistency, reliability and comparability as patenting systems across nations differ in their application of standards, system of granting patents, and value of protection granted (Ahuja and Katila, 2001). For the firms in the sample, yearly patent counts were obtained. Patents that are granted are counted and carries the original application date. This date was assigned to a granted patent to the particular year when it was originally applied for to ensure consistency in the treatment of all patents and controls for differences in delays that may occur in granting patents after the application is filed (Desyllas and Hughes, 2010).

6.3.6 OECD Citations Database

The data on citations to patents has been collected from the OECD Citations database (2018). It provides data on patent citations from PATSTAT database which is EPO's Worldwide Statistical Patent Database and gives an extensive set of information on citations made and received by patents filed worldwide. The database covers patent citations from all patent offices, including EPO, USPTO and JPO. It includes information on data items such as, patent publication number, name of patenting firm, description of patent, patent publication date, patent grant date, list of patents cited in a particular patent, number of cited patents and number of citations received by a patent. The number of citations a given patent receives (forward citations) mirrors the technological importance of the patent for the development of subsequent technologies and also reflects to a certain extent the economic value of inventions (Trajtenberg, 1990; Hall et al., 2005). The citations data is matched with the patent data through patent publication number which is the same as the patent application number and serves as an identifier in the OECD Patent database. For each published patent, the citations received by a patent are counted. Publication typically occurs 18 months after the filing date of the patent and patents keep receiving citations over a long period of time. The citations data is observed from patent publication date up to the last year of the available data, that is, 2017, when the data ends.

6.3.7 Hoover's Online

Hoover's Online is also an online database maintained by Bureau van Dijk which covers information on public and private companies worldwide. The database is used as a complementary to FAME database that enables cross checking corporate parent names, subsidiaries and ownership information on the companies in the sample.

6.3.8 Midas List

The Midas list is used to get information on the reputation of investors affiliated with a firm (Forbes, 2018). It gives recognition to the top corporate venture capitalists and venture capitalists who make deals in the technology companies and create value for investors. First, a company is considered a corporate venture capital/venture capital deal if it exited in the last five years with a combined value of $200 million. Private companies valued at $400 million or greater are also considered. This information is collected from Dow Jones VentureSource data and lists. Next, each investment deal is ranked according to deal value, size of exit or private valuation and stage of investment. Then the number of investments with highest returns are aggregated for each investor to determine their deal attribution score which forms a deal metric ranking against his or her peers. After this, the total number of qualifying deals, that is, deal count per each investment is considered to determine each investors deal count ranking. The corporate/venture capitalists are ranked on the basis of (1) deal metrics and (2) deal count. For example, if three corporate/venture capitalists are investing in the same company at different stages, then each investor who invested in a particular company receives a score for their deal based on the number of rounds of investment, ownership, board seat and the gains from the investment. This process is repeated for all companies attributed to each corporate/venture capitalist which amounts to a total deal attribution score. This score determines the ranking by deal metrics for each individual. Next the corporate/venture capitalists are ranked by deal count. The total deal count scores are calculated by the number of exits and private deals. Together, the rankings by deal metric and deal count, coupled with a review by experienced institutional investors and corporate/venture experts, determines a corporate/venture capitalists position on the Midas list. The Midas list also provides the name of the firm and the individual investor affiliated with a firm[10]. The study therefore uses the Midas list published by Forbes to identify investors each year between 2008 and 2016.

6.3.9 Fortune's Most Admired Companies Survey

The Fortune magazine publishes a list of firms deemed as World's "Most Admired Companies" every year since 1983. This designation is based on surveys that ask more than 8000 financial analysts, senior executives and outside directors to rate the 10 largest companies in their own industry on 8 reputational indicators on a scale of 0 (poor) to 10 (excellent). The

[10] The method of formulating the Midas list was taken from the original website *http://submitmidasdata.com/*.

characteristics include the quality of management; the stewardship of corporate assets; financial soundness; the value of long-term assets; the quality of the products or services; innovativeness; the ability to attract, develop and keep talented people; and the responsibility to the community and the environment. The eight scores are then averaged to arrive at a final score (Filbeck, Gorman and Zhao, 2013).

6.4 Sample Construction

The research constructed a sample by matching and integrating information from the databases described in the sections above. I begin by creating two separate samples: (1) population of firms on potential high technology targets, and (2) population of firms on potential high technology and non-high technology acquirers. The construction of each of the samples is explained in the following sub-sections.

6.4.1 Sample of Target Firms

The procedure for constructing the sample involves a series of stages. In the first stage, the population of high technology firms in the UK from 2008 to 2016, is extracted from FAME. According to Hall and Vopel (1996) the high technology industry consists of firms operating primarily in SIC 28 Chemicals and Allied Products; SIC 35 Industrial and Commercial Machinery and Computer Equipment; SIC 36 Electronics and Electrical Equipment; SIC 37 Transportation Equipment; SIC 38 Measuring, Analysing and Controlling Instruments, Photographic, Medical and Optical Goods; SIC 48 Communications; SIC 73 Business Services and SIC 87 Engineering, Accounting, Research, Management and Related Services[11]. The high technology sector is selected for the following reasons:

1) There have been a significant number of acquisitions in the high technology industry (Desyllas and Hughes, 2010; Chondrakis, 2016; Bena and Li, 2014) to allow for a large sample to study the choice of an acquisition target.

[11] A complete list of targets' 2-digit industry SIC codes is attached in the Appendix A.

2) Firms in the high technology industry receive corporate venture capital backing (Graebner et al., 2010) for developing competing technologies.
3) High technology firms are increasingly engaged in alliances (Stuart, 2000) and there have been a sufficient number of inter-organisational relationships in the industry to study their influence on the probability of an acquisition.
4) Technological innovation is a crucial factor for firms in the high technology industry (Hagedoorn and Cloodt, 2003). Technology firms that receive corporate venture capital backing are particularly vibrant sources of technical innovation and new products and produce more inventions from each dollar invested (Graebner et al., 2010). Additionally, firms engaged in alliances lead to innovation growth (Stuart, 2000). This makes high technology industry an appropriate context to explore the influence of inter-organisational relationships of firms on the post-acquisition innovation performance of acquired (merged) firms.
5) The high technology industry is well suited for the study because the firms in this industry patent their inventions and receive citations on their inventions. An advantage of this is to use patent and citations data to operationalize the variables on the innovation performance of acquired (merged) firms. This plays a significant role in indicating important aspects of innovation performance in terms of quantity and quality of output produced (Hagedoorn and Cloodt, 2003; Stuart, 2000).

FAME provides information on a population of 6420 public and private high technology firms in the UK with complete information on financial ratios and performance, size, R&D expense and industry items used as control variables for the analysis. In the second stage, the information on mergers and acquisitions is retrieved from the M&A deals section in Thomson One. Events that involved the acquisition of public and private high technology firm in the UK by worldwide public acquirers from all industry sectors are included. In the third stage, information on firms receiving CVC investments is collected from Thomson One Private

Equity and matched with the sample of firms from FAME. In the fourth stage, information on firms engaged in alliances is gathered from SDC Platinum and matched with the sample of firms from FAME. Lastly, this sample of potential targets from FAME was matched with patent and citations data. This has been explained in section 6.3.5 and 6.3.6. The sample of firms from FAME is matched with the other databases (Thomson One, Thomson One Private Equity and SDC Platinum) using company names as an identifier as there were no other common identifiers available between these. In order to do this, I used v-lookup in excel and developed a string of letters (maximum 5 letters) to match company names. This was checked manually for any errors or matches that may have been missed.

The final data set consists of 6420 firms, of which 682 were completely acquired in the observation period 2008 – 2016, while the rest were not acquired. These 6420 firms are engaged in a total number of 2145 CVC investments and a total number of 6853 alliances during the period of analysis. This means the firms are engaged in a total number of 8998 inter-organisational relationships. Of the 682 acquired firms, 201 (29.47%) of them are engaged in inter-organisational relationships, that is, CVC investments and alliances.

6.4.2 Sample of Acquiring Firms

The population of high technology and non-high technology firms in the UK is collected from FAME. The acquirers comprise public firms in the high technology and non-high[12] technology industries in the UK. Next, the information on domestic acquisitions by public acquirers in the UK is collected from Thomson One which is maintained by Thomson Reuters. The sample consists of domestic acquisitions involving deals where the acquiring firms are in the high technology and non-high technology industries that acquired firms in the high technology industries in the UK, during the period 2008 – 2016. This information is matched with the sample of potential acquiring firms from FAME. The same procedure was

[12] Non-high technology industries comprise industries excluding the high technology sectors.

followed, using v-lookup in excel and matching on company names as identifiers. Then the sample from FAME is matched with patent and citations data as described in the sections above (sections 6.3.5 and 6.3.6). FAME gives information on a population of 3296 public firms in high technology and non-high technology industry sectors in the UK with complete information on the financial and accounting control variables employed in the analysis. Of these, there are 102 different public UK acquirers in the high technology and non-high technology industries that carried out at least one acquisition during the period 2008 – 2016.

After the two samples, one on targets and the other on acquiring firms has been obtained, the next process is to apply coarsened exact matching method on each (a detailed explanation on the method is given in section 6.2.8). Eventually, the target and acquirer samples are merged together into one unique sample, but it is important to explain these separately at this stage for the understanding of the reader. The next sections explain the matching process applied on each of these in depth.

6.4.3 Coarsened Exact Matching on Target Firm Sample

In this study, the coarsening is based on size of firms as measured by the natural logarithm of number of employees, profitability of firms as measured by the return on assets, 4-digit industry SIC codes, and year of observation. The choice of covariates used for coarsening depends on the variables known to be related to the outcome (Stuart, 2010). The CEM procedure selects firms at random without replacement that match the acquired firm on profitability as measured by return on assets, firm size as measured by number of employees, 4-digit industry SIC codes and observation year[13].

[13] As mentioned in Blackwell et al (2010), CEM uses maximal information, resulting in strata that may include different number of treated and control units. To compensate for the differences in the sizes of the strata, the CEM method also produces weights to be used in subsequent analysis. This is the best option as stated in the manual for CEM. More information can be found in the document by Blackwell, Iacus, King and Porro (2010). The strata return different case to control ratios where the minimum choice of ratio by the algorithm is 1:1 and the maximum choice of ratio is 1:24. There is no rule around the choice of ratio used to match an acquired firm with the controls

For the natural logarithm of number of employees, natural breaks/cutpoints in the data occur at (0.53, 1.06, 1.59, 2.12, 2.65, 3.18, 3.71, 4.24, 4.77, 5.31, 5.84, 6.37, 6.90, 7.43, 7.96, 8.49) and these are used as boundaries for the matching. For return on assets, natural breaks/cutpoints in the data occur at (-181.59, -164.64, -147.70, -130.75, -113.81, -96.86, -79.91, -62.97, -46.02, -29.08, -12.13, 4.82, 21.76, 38.71, 55.65, 72.60, 89.55) and these are used as boundaries for the matching.

The overall imbalance is given by the L1 statistic (Iacus et al., 2009) which is based on the difference between the multidimensional histogram of all pre-treatment covariates in the treated group and that in the control group (Blackwell et al., 2009). The imbalance for 4-digit industry SIC, size and profitability is L1 = 0.97. The L-statistic measures imbalance between 0 to 1 and a perfect global balance is indicated by L1 = 0, with a maximum of L1 = 1, which indicates complete separation. The L1 value is not valuable on its own, but rather as a point of comparison between matching solutions. After the matching solution is obtained, its L1 value will be compared to 0.97 to check the increase in the balance due to the matching solution from that difference.

After matching on the pre-treatment variables, that is, 4-digit industry SIC codes, size and profitability, the output gives the number of observations in total, matched, and unmatched by treatment group and gives information about the quality of the matched data[14] (Blackwell et al., 2009). An exact match was obtained on 4-digit industry SIC codes and natural breaks in the data were used to match on firm size and profitability. The L1 statistic is 0.85 after matching. By comparing the imbalance results to the original imbalance (L1 = 0.97), it can be seen that a good match can produce a substantial reduction in imbalance in the distribution of

but using fewer controls to match to each acquired firm produces large standard errors (Rogan and Sorenson, 2014). I matched each case with 5 controls.

[14] A common feature of acquired firms that fall out of the sample reveals very small firm size (reporting 0-3 employees) compared with the final sample of matched acquired firms.

the data[15]. The variables are still included as controls in the regression analysis to take into account remaining imbalances. CEM also generates weights for use in the evaluation of imbalance measures and estimates of the causal effect.

6.4.4 Coarsened Exact Matching on Acquiring Firm Sample

For the acquiring firms, I used the same CEM procedure, selecting firms at random without replacement that matched the acquiring firm on profitability as measured by return on assets, firm size as measured by number of employees, 4-digit industry SIC codes and observation year. Exact matches are obtained on 4-digit industry SIC codes and year of observation. For firm size and profitability, natural breaks in the data are used to create the coarsening as it is a better approach than using fixed bin sizes that disregard meaningful breaks in the data (Blackwell, 2010). For the natural logarithm of number of employees, natural breaks/cutpoints in the data occur at (0, 0.75, 1.49, 2.24, 2.98, 3.73, 4.48, 5.22, 5.97, 6.71, 7.46, 8.20, 8.95, 9.70, 10.44, 11.19) and these are used as boundaries for the matching. For return on assets, natural breaks/cutpoints in the data occur at (-299.11, -275.33, -251.56, -227.78, -204.00, -180.22, -156.45, -132.67, -108.89, -85.11, -61.34, -37.56, -13.78, 9.995, 33.77, 57.55) and these are used as boundaries for the matching.

After matching on the pre-treatment variables, that is, 4-digit industry SIC codes, firm size, firm profitability and observation years, the output gives useful information about the match. It gives the number of observations in total, matched and unmatched by treatment group and gives information about the quality of the matched data[16] (Blackwell et al., 2010). The

[15] The advantage of CEM is that the user can specify their own bin sizes although the authors (Blackwell et al., 2009) encourage users to use the natural breaks in the data. I also attempted to use fewer bins in matching to check if it improves the imbalance. By using fewer bins of approximately 20 equally spaced out bins improved the imbalance, L1 statistic = 0.77. However, it resulted in a loss of 246 acquired firms. The number of acquired firms fell to 436. Therefore, it was best to use the natural breaks in the data for firm size and profitability and to do an exact match on 4-digit industry SIC codes and observation years.

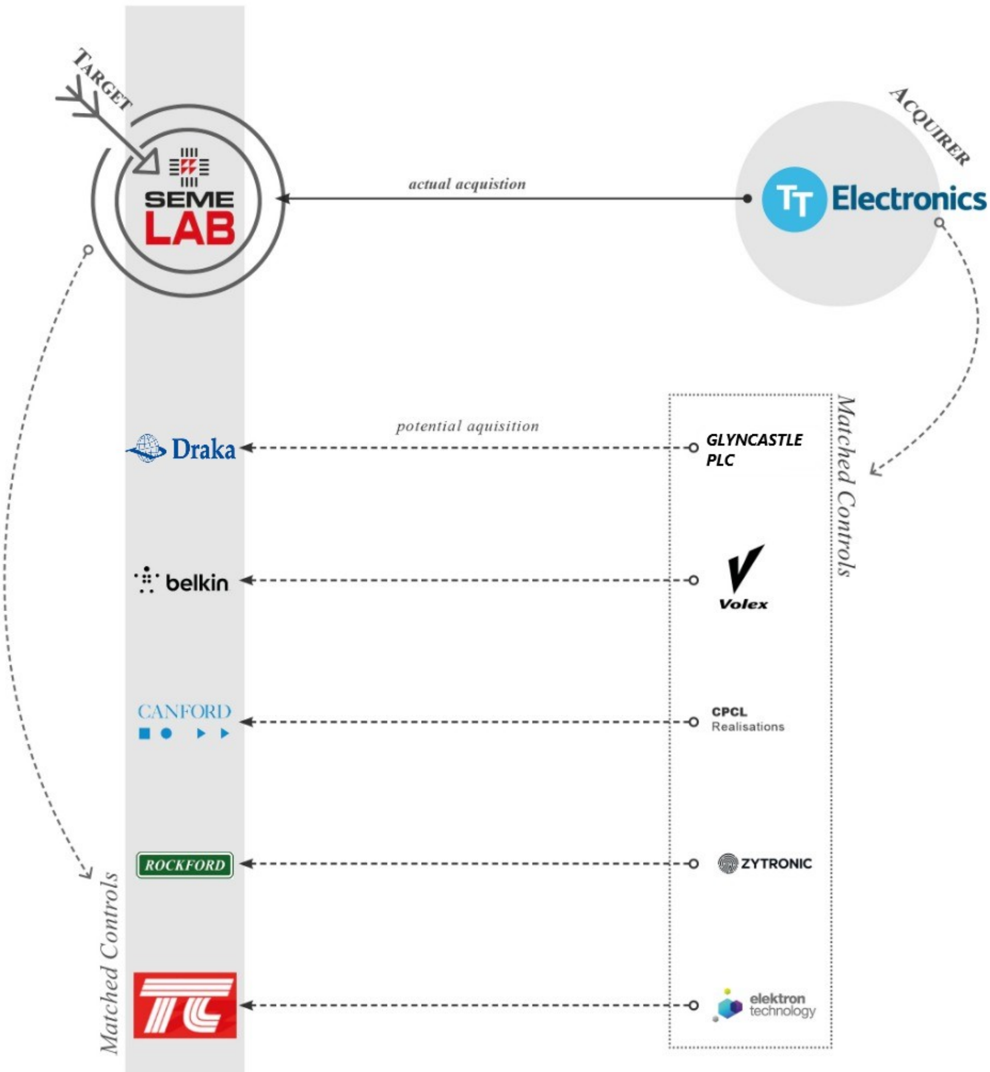
[16] The strata return different case to control ratios where the minimum choice of ratio by the algorithm is 1:1 and the maximum choice of ratio is 1:10. Each case was matched to 5 control acquirers. More information on matching cases-to-controls is given in Blackwell et al (2010).

imbalance for the 4-digit industry SIC, firm size, firm profitability and observation years is L1 = 0.97. The L1 statistic is 0.84 for the matched data. A comparison of the imbalance results to the original imbalance shows that a good match results in a substantial reduction in the imbalance of the distribution of the data (Blackwell et al., 2010). CEM also generates weights which can be incorporated in the analysis of imbalance measures and estimates of the causal effect (Blackwell et al., 2010). After pre-processing the data with CEM, a Poisson regression with triple difference analysis is applied to estimate acquisition performance.

6.4.5 Designing combinations of merged and non-merged firms

After making separate matched samples of acquiring and acquired firms, I brought the two together in one dataset. To create an appropriate set for comparison, the sample constructed was matched to merged firms with a set of counterfactual acquisitions (controls) – combinations of firms that could have happened. To make combinations of deals that could have happened, the matched potential acquirers were randomly combined with the matched potential acquired firms to generate counterfactual deals. The choice set involves creating a number of counterfactual acquisitions by creating different pairs of firms that could have been acted as acquiring and acquired firms. For each actual deal, at least one matched potential acquirer was randomly combined with at least one matched potential acquired firm to design deals that could have occurred. The research design is similar to the study by Rogan and Sorenson (2014). Figure 6.1. illustrates this with the help of an example taken from the original dataset constructed for the research.

Figure 6.1. Acquirer-target actual deal and combinations of synthetic mergers. The example is taken from the dataset constructed for Study 3 where the acquiring and acquired firms are based in UK.



6.5 Variables and Measurement

6.5.1 Study 1: Target Firm Selection Model

Dependent variable. Acquisitions are defined as deals where the acquiring firm increases its ownership and acquires at least 50% of the target firm’s shares as a result of the takeover (Desyllas and Hughes, 2009). The dependent variable is a binary variable that takes the value 1 when a firm is acquired and 0 otherwise.

Independent variables. The first independent variable is a count, the *total corporate venture capital (CVC) investments of firms,* measured as the number of CVC investments a firm *i* received in the 3 years prior to an acquisition year *t* of observation. Vrande and Vahaverbeke (2013) use a similar proxy. The second independent variable is a count, the *total alliances of firms,* measured as the number of alliances of a firm *i* in the 3 years prior to an acquisition year *t* of observation. Schilling (2009) proxy in a similar way. These include joint venture, licensing, marketing, manufacturing and R&D partnerships between companies.

Moderator variables. The first moderator variable is *start-up,* which is a binary variable coded 1 if age of a firm is less than or equal to 7 years and it is 0 if firms are aged above 7 years. Firm *age* is measured as the difference between the year of observation and the founding year of the firm (Benson and Ziedonis, 2009). This is a suitable age because by the age of 5, many firms have failed to build strong market positions and have become extinct. On the other hand, firms up to the age of 12 have survived the liability of newness but have not yet "reached the mature stage where they resemble established firms" (Bantel, 1998).

The second moderator variable is *reputation of CVC investors affiliated with a firm* which is a dummy variable that takes the value 1 if at least one of the corporate investors affiliated with a firm is listed on the Midas list published by Forbes magazine and is 0 otherwise. Although studies have not used the Midas list published by Forbes specifically, this gives important information about the reputation of CVC investors[17].

The third moderator variable is *reputation of strategic alliance partners affiliated with a firm* which is a dummy variable that takes the value 1 if at least one of the alliance partners

[17] Studies are increasingly measuring reputation by the visibility in media. For example, Dimov et al. (2007) measure reputation by media visibility by the number of times a firm is mentioned in *The Wall Street Journal*. Another example is the study by Brammer and Pavelin (2006) who use Britain's Most Admired Companies list to gather information on reputation of firms.

affiliated with a firm is listed on the Fortune's "Most Admired Companies" survey and is 0 otherwise (Filbeck et al., 2013).

Control variables. I included *patent stock* as a control variable because patents are seen as attractive assets and a rich source of technological information (Grimpe and Hussinger, 2014). By filing a patent application, an entrepreneur reveals information about the technologies under development in firms, which signals firm quality (Lahr and Minha, 2016; Hsu and Ziedonis, 2008, 2013). The variable is measured as the number of successful patent applications, or granted patents[18], of a firm *i* in the 3 years prior to an acquisition year *t* of observation. The variable has been transformed in logarithm[19] due to skewness.

I control for other additional firm characteristics which might influence a firm's acquisition activity. These include firm size, economic performance and availability of financial resources (Palepu, 1986; Powell, 1997; Granstrand and Sjolander, 1990; Agrawal and Jaffe, 2003; Ambrose and Megginson, 1992). The variable *size* is employed to measure firm size which is given by the number of employees in a firm as it provides the best coverage for the firms included in the sample. The variable has been transformed in logarithm because of skewness. Mazzola et al (2016) also use number of employees as a proxy for firm size. The economic performance is measured by the variable *profitability*. This is calculated as the return on total assets[20]. Dickerson et al (2002) use a similar proxy for firm performance. The financial status of firms is measured by *liquidity* which reflects a firm's ability to meet its short-term

[18] The granted patent carries the date of the original application. This date is used to assign a granted patent to the particular year when it was originally applied for. This procedure permits consistency in the treatment of all patents and controls for differences in delays that may occur in granting patents after the application is filed (Ahuja and Katila, 2001).
[19] To transform the variable into logarithm, the formula *ln (1+x)* was used.
[20] This is taken from FAME and is defined in the database as the ratio of profit before tax to total assets. Profit before tax is defined in the database as operating profit plus total of other income and interest received and the difference between the interest paid (to bank, hire purchase, leasing, other interest) and the profit on sale of operations, costs of reorganisation, profit on disposal, and other exceptional items. Total assets is described in the database as the sum of fixed assets and current assets. As described in FAME, fixed assets include tangible assets, land and buildings, freehold land, leasehold land, fixtures and fittings, plant and vehicles, other fixed assets, intangible assets and investments. Current assets include stock, finished goods, trade debtors, bank deposits, group loans, director's loans, prepayments, deferred taxation and investments as described in FAME.

obligations from its current assets (Hasbrouck, 1985; Harris, Stewart, Guilkey and Carleton, 1982). This is calculated by the ratio of current assets to current liabilities. Desyllas and Hughes (2009) use a similar proxy. There is evidence for the existence of some influential outliers due to which the data are winsorized at 1% (0.5% from each side).

I also included *R&D expenditure* as a control variable and follow Desyllas and Hughes (2009) to correct for missing values of R&D expenditure. R&D expenditure is assumed immaterial whenever it is not reported but where data on most of the financial variables is available (Hall, 1999). A dummy variable, *R&D missing*, is employed for missing R&D values which equals 1 when R&D is missing and is 0 otherwise. *Private Firm Status* is also used as a control variable to account for the acquisitions of public and private firms (Capron and Shen, 2007). It takes the value 1 when a firm is privately held and is 0 if a firm is publicly held. *Industry dummies* based on the first two digits of the industry SIC are employed in the regression analysis to account for industry-wide differences in acquisition likelihood. *Year dummies* are included to account for the period effects. Table A-1 in Appendix A shows the dependent, independent, moderator and control variables of the target firm selection model.

6.5.2 Study 2: Acquired Firm Innovation Performance Model

Dependent variable. This is given by the variable *Innovation Performance*. The analyses of the acquisition effect on innovation output post-acquisition centres on two measures of innovation performance: (1) patent count, and (2) citations received per patents. This is constructed for acquired and non-acquired (control sample) firms.

I examined successful patent applications granted to a firm *i* as indicated by the number of patent applications filed in each year *t* of observation. Patents are considered by application date but only patents which are actually granted are counted (Desyllas and Hughes, 2010). The method is similar to that done in prior studies (Ahuja and Katila, 2001; Seru, 2014). The application date is preferred to grant date because the actual time of inventions is closer to the application date than to the subsequent grant date which depends upon the review process of the patent office (Desyllas and Hughes, 2010; Hall et al., 2005).

The innovation performance is also operationalized by the number of citations received per patent and is constructed by taking the total number of citations received on all the patents produced by a firm *i* in a year *t* of observation. The data includes information on citations received per patent from the publication date of the patent up to 2017 which is the year when the data ends. There is a fall in the number of citations received per patent in the later years as the patents granted in recent years have not been available long enough to receive citations by future patents (Dushnitsky and Lenox, 2005b).

Using patents and citations as a measure of *innovation performance* entails both strengths and weaknesses. Patents are recognised as rich source of data to study innovation and technological significance, which depicts the *novelty* of an invention (Hall et al., 2005). They are directly associated with the inventiveness of firms and are granted only for *'non-obvious'* advancement in innovation (Ahuja and Katila, 2001). Patents award exclusive rights to the inventors and contain detailed information on the innovation, assignees, and geographies which indicates its *usefulness* and potential commercial and *economic value* (Hall et al., 2005). The patent citation measure has the advantage of incorporating an indication of each patent's technical significance and economic value (Paruchuri et al., 2006) as patented innovations are a result of costly R&D conducted by firms (Hall et al., 2005). Moreover, citations to a patent typically keep coming over the long run, giving plenty of time to dissipate the original uncertainty regarding both the technological growth and the commercial worth of the patented innovation (Hall et al., 2005). Thus, if a citation is received years after a patent is granted, it indicates that the latter had indeed proved to be economically valuable (Hall et al., 2005).

There are some limitations of using patent and citations data too. Not all inventions are patentable because they do not meet the patentability criteria or because they are not patented

(Hall et al., 2005; Ahuja and Katila, 2001). Some inventors rely on secrecy to protect their innovations (Hall et al., 2005; Seru, 2014). Firms in different industries might not have patents for all their innovations and the patent and citation intensities can vary across industries (Seru, 2014; Ahuja and Katila, 2001). Patents measure only successful innovations, for which industry and year effects are included in the regressions to account for any differences in specific patterns.

Independent variables. The *total corporate venture capital (CVC) investments of firms,* is measured as the number of CVC investments a firm *i* received in a particular year *t* of observation. The *total alliances of firms,* is measured as the number of alliances a firm *i* engages in a particular year *t* of observation. The study controls for the same variables used in the target firm selection model. Table A-2 in Appendix A lists the dependent, independent and control variables of the acquired firm innovation performance model.

6.5.3 Study 3: Merged Firms' Innovation Performance Model

Dependent variable. This is given by *Innovation performance* which is operationalised by patent count and forward citations. For the merged (acquired and acquiring) firms, I summed the number of successful patent applications of each of the acquiring and acquired firms. Patents are counted for each firm *i* in year *t* of observation and successful patent applications granted are indicated by one or more patent applications. The innovation performance of merged firms is proxied by citations received per patents as well: For merged firms, I summed the number of citations received on all the patents produced by each of the acquiring and acquired firms. Citations per patent are computed for each patent of a firm *i* in year *t* of observation. The same procedure is used to construct this measure for the controls (non-merged firms).

Independent variables. This is given by the CVC investments and alliances of an acquired firm. The variable is measured as the number of CVC investments an acquired firm *i* received in year *t* of observation. The variable on alliances is measured as the number of alliances in an acquired firm *i* in year *t* of observation.

Control variables of the acquiring firms. The study controls for acquiring firm characteristics which include firm *size* as measured by number of employees. This is controlled as large firms are likely to be acquirers (Bena and Li, 2014). Economic performance of acquiring firms is given by the variable *profitability* which is measured as return on total assets. High performing firms are likely to be acquirers (Bena and Li, 2014) due to which profitability is controlled in the analyses. *Liquidity* is measured as the ratio of current assets to current liabilities and *R&D expenditure* is also employed as control variable to account for input into research and development processes undertaken in firms and is as reported in the FAME database. The industry relatedness is captured by the variable *related* which is a dummy variable coded 1 if the acquiring and target firms are in the same 4-digit industry SIC codes and 0 otherwise. This variable is incorporated into the analyses to take into consideration acquisitions of targets functioning in similar and different business domain and it might be that synergies are difficult to achieve when the two merging firms are operating in different industries (Mitchell and Shaver, 2003). The standard *industry* and *year* dummies are also included as controls. The data have been winsorized at 1% level (0.5% from each side) due to the presence of some outliers. Table A-3 in Appendix A displays the dependent, independent and control variables of the merged firm's innovation output model.

CHAPTER 7

RESULTS

7.1 Introduction

This chapter provides a detailed account of the descriptive statistics, correlations of the variables and the results of the analysis of each study separately in three subsections. The first subsection describes the sample and results of the target firm selection model (study 1); the second subsection describes the sample and findings of the acquired firm innovation performance model (study 2); and the third subsection describes the sample and results of the merged firm's innovation performance model (study 3).

7.2 Study 1: Target Firm Selection Model Results

7.2.1 Coarsened Exact Matching

The key aim of coarsened exact matching is to balance the data set by matching the firms in the treated and control groups so that they are as similar as possible. The data is matched on pre-treatment observations of firm size which is measured by the natural logarithm of number of employees, firm profitability which is measured by the return on assets, 4-digit industry SIC codes and acquisition year. The output from the matching process shows the number of observations matched and retained as well as those which were pruned because they were not comparable (Blackwell et al., 2009).

Prior to matching, the total number of firms in the sample was 6,420 out of which 682 firms were acquired. After matching, the total number of firms in the sample is 2,302 out of which 477 firms were acquired. Table 7.1. displays a comparison of the yearly distribution of acquisitions before and after CEM. For each deal there is one observation for the acquired firm and multiple observations for the control target firms. The research design is similar to the study by Bena and Li (2014).

Table 7.1. Acquisitions sample of the target firm selection model before and after CEM.

	Before CEM			After CEM		
Year of Obs.	Not Acquired	Acquired	Total Obs.	Not Acquired	Acquired	Total Obs.
2008	3767	133	3900	428	85	513
2009	3971	44	4016	183	32	215
2010	4096	57	4153	284	46	330
2011	4181	60	4241	325	38	363
2012	4274	71	4345	358	52	410
2013	4439	87	4526	629	79	708
2014	4492	69	4561	416	46	462
2015	4594	97	4690	546	74	620
2016	2942	64	3006	152	25	177
Total Obs.	36,756	682	37,438	3,321	477	3,798

7.2.2 Descriptive Statistics

Table 7.2. shows a comparison of the descriptive statistics of the pre-treatment variables before and after CEM. The mean value and standard deviation of the sample is reduced by the CEM method and this is due to coarsening of the data (Iacus et al., 2009; Blackwell et al., 2009). For the acquired firms, the standard deviation of firm size was 1.65 (expressed in logarithm) before CEM which is reduced to 1.52 (expressed in logarithm) after matching. The standard deviation of profitability of acquired firms was 40.24 before matching and reduces to 26.21 after CEM. The total number of observations before matching on the pre-treatment variables was 33,919. After an implementation of CEM, the total number of observations are 3,798. A total of 30,121 observations were unmatched.

Table 7.2. Descriptive statistics of target selection model pre-treatment variables before and after CEM.

	Before CEM		After CEM	
Variable	Treated group	Control group	Treated group	Control group
Size (mean)	4.42	4.18	4.42	4.35
Size (std. dev.)	1.65	1.55	1.52	1.06

Profitability (mean)	0.28	4.66	6.52	7.88
Profitability (std. dev.)	40.24	30.62	26.21	15.81
Panel sample obs.	682	33237	477	3321
Number of firms	682	5738	477	1825

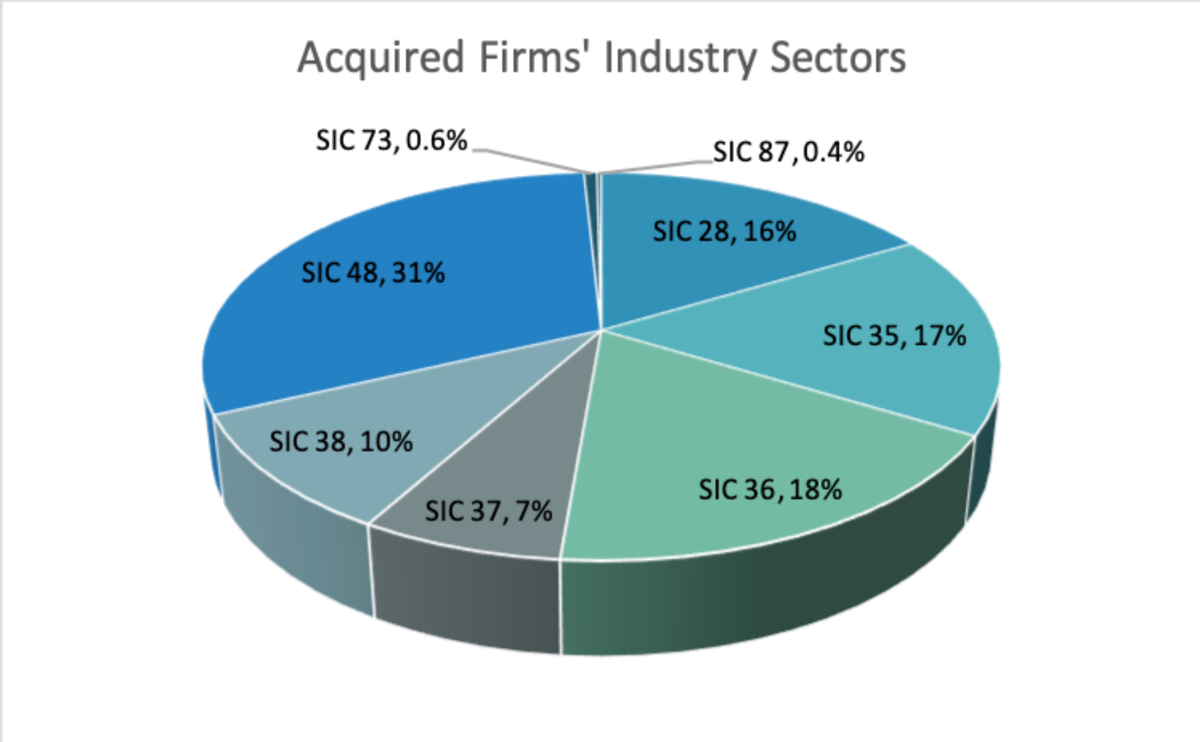
Table 7.3. shows the descriptive statistics of the sample after CEM from the year 2008 – 2016, which includes information on both acquired and non-acquired firms. During the observation period, of the 477 acquired firms, 139 (29.14%) of them are engaged in CVC investments and/or alliances. Firms were engaged in 1126 inter-organisational relationships at the time of acquisition. Firms were involved in 289 CVC investments at the time of acquisition with an average of 3.40 CVC investment relationships. Firms were involved in 837 alliances with an average of 5.02 strategic alliance relationships. The acquired firms spent on average 2191 million GBP on R&D and were granted 3.62 patents per year, as compared to the matched control firms. On average, each acquired firm had a total of 817 employees (4.42 expressed in logarithm) and profitability (return on assets) of 6.52%, which indicates slightly larger firm size and lower ROA compared to their matched control firms. The descriptive statistics also suggest that 94% of the acquired firms are private and 6% are public. The acquired firms are on average, 17.6 years of age, with 32% being start-ups, as compared to their matched industry counterparts.

The pie chart in Figure 7.1. represents the population of acquired high technology firms in UK, including 16% in chemicals and allied products (SIC 28), 17% in industrial and commercial machinery and computer equipment (SIC 35), 18% in electronic and other electrical equipment and components (SIC 36), 7% in transportation equipment (SIC 37), 10% in measuring, analysing and controlling instruments; photographic, medical and optical goods (SIC 38), 31% in communications (SIC 48), 0.6% in business services (SIC 73) and 0.4% in engineering, accounting, research, management, and related services (SIC 87).

Table 7.3. Descriptive statistics of target selection model after CEM.

	All Firms		Acquired Firms		Non-Acquired Firms	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Acquisition	0.13	0.33	1.00	0.00	0.00	0.00
Private Firm Status	0.95	0.22	0.94	0.23	0.95	0.22
Liquidity (log)	0.32	0.79	0.21	0.87	0.33	0.78
Size	530.65	5508.94	816.67	6400.40	489.57	5368.61
Size (log)	4.36	1.13	4.42	1.52	4.35	1.06
Profitability	7.71	17.46	6.52	26.21	7.88	15.81
CVC Investments	0.08	0.68	0.38	1.54	0.03	0.41
Alliances	0.22	1.34	0.61	2.11	0.16	1.17
R&D Expenditure	1382.41	28721.07	2191.93	39438.97	1266.14	26838.43
R&D Missing	0.85	0.35	0.83	0.38	0.86	0.35
Firm Age	22.60	19.58	17.56	20.33	23.32	19.36
CVC Partner Reputation	0.00	0.04	0.00	0.06	0.00	0.03
Alliance Partner Reputation	0.00	0.06	0.02	0.13	0.00	0.04
Patent Stock	1.24	19.35	3.62	48.54	0.90	9.45
Patent Stock (log)	0.09	0.54	0.15	0.72	0.08	0.50
Start-Up	0.19	0.39	0.32	0.47	0.17	0.37
Panel Sample Obs.	3798		477		3321	
No. of Firms	2302		477		1825	

Figure 7.1. Distribution of High Technology Acquired Firms in the UK.



7.2.3 Correlation

Table 7.4. displays the pairwise correlations between the variables after CEM. The low correlations between the independent and control variables of the model suggest the absence of multicollinearity of variables in the analysis. The correlations show that there is a positive and significant correlation between acquisition and CVC investments (0.1722, $p<0.05$), which suggests that firms backed by CVC investments are likely of being acquired. Alliances and acquisitions exhibit a positive and significant correlation (0.1105, $p<0.05$), which explains that firms engaged in alliances are likely of being acquired. This means both types of relationships convey similar information to external parties – both alliances and CVC contribute to a firm's visibility and increase its attractiveness to acquirers. The correlation between CVC investments and alliances is low and positive but not statistically significant. CVC and alliances are pursued to achieve different goals and objectives. In case of alliances, a firm may engage in joint learning, co-development and commercialization of technologies with its partners (Gulati,

1998). In case of CVC, an investor seeks financial returns on investments by taking an active role in managing the funded venture through board affiliations or informal consultations (Dushnitsky, 2012). It is possible that for CVC investors making the investments, gaining returns on investment play a more important role. Also, firms making CVC investments pursue these with the objective of exiting the funded venture at some stage (Dushnistky and Lavie, 2010). Alliance partners may just partner to access complementary resources and achieve their own objectives (Gulati, 1998). CVC and alliances offer complementary benefits which gives way to redundancy as multiple alliances fail to offer novel opportunities to commercialize technologies from the funded ventures (Dushnitsky and Lavie, 2010). As CVC investors establish presence in the market by building an extensive alliance portfolio, each additional increase in the number of alliances offers only a marginal contribution to the firm's visibility and attractiveness to fund prospective ventures (Dushnitsky and Lavie, 2010). As a result, the positive impact of each additional alliance on CVC lowers due to complementarity and visibility. This explains the lower association between CVC and alliances.

The size of firms was used as a pre-treatment variable and after matching, it depicts a positive correlation with acquisition but it is not statistically significant. Profitability of firms was also employed as a pre-treatment variable in the process of matching and it shows a negative correlation with acquisition but it is not statistically significant. The correlation between firm age and acquisition is negative and statistically significant (-0.0975, $p<0.05$), indicating that old firms are less likely of being acquired. On the other hand, the correlation between start-up and acquisition shows a positive and statistically significant relationship (0.1365, $p<0.05$), which illustrates that young firms (less than 7 years of age) are more likely of being acquired.

The correlation between CVC partner reputation and acquisition is positive but not statistically significant. However, the correlation between CVC investments and CVC partner reputation is positive and statistically significant (0.5107, $p<0.05$), which shows that firms backed by CVC investments are affiliated with high reputation CVC partners. Acquisition and alliance partner reputation show a positive and statistically significant relationship (0.0866, $p<0.05$), which suggests that firms affiliated with high reputation alliance partners are likely of being acquired. The correlation between alliances and reputation of alliance partner is positive and statistically significant (0.4995, $p<0.05$), which shows that firms engaged in alliances are affiliated with reputable alliance partners. Patent stock and acquisition indicate a positive and statistically significant correlation between the two (0.0413, $p<0.05$), which explains that firms with patents are likely of being acquired. There is a positive and statistically significant correlation between CVC investments and patent stock (0.0540, $p<0.05$), which means that firms receiving CVC investments produce patents. Alliances and patents also show a positive and statistically significant correlation (0.0978, $p<0.05$), which suggests that firms engaged in alliances are also involved in patenting activities. There is a statistically significant positive correlation between R&D expenditure and patent stock (0.1368, $p<0.05$), which indicates that firms with R&D input produce output in terms of patents. There is a statistically significant negative correlation between patent stock and the dummy capturing missing R&D expenditure (-0.0891, $p<0.05$), which means that firms without R&D also do not produce patents.

Table 7.4. Correlation of target selection model after CEM (panel sample obs. = 3798, total no. of firms = 2302; acquired firms = 477; non-acquired firms = 1825). Pairwise correlations show significance at the 5% level and are marked by an asterisk (*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Acquisition	1													
(2) CVC Investments	0.1722*	1												
(3) Alliances	0.1105*	0.0033	1											
(4) Liquidity	-0.0514*	-0.073*	-0.0529*	1										
(5) Size (log)	0.0206	0.0017	0.1937*	-0.0423*	1									
(6) Profitability	-0.0257	-0.1325*	-0.0463*	0.2802*	0.0590*	1								
(7) R&D Expenditure	0.0107	-0.001	0.2916*	-0.0337*	0.1582*	-0.0097	1							
(8) R&D missing	-0.0299	-0.0625*	-0.0177	-0.0890*	-0.1613*	-0.0267	-0.1164*	1						
(9) Firm age	-0.0975*	-0.0673*	-0.0432*	0.1442*	0.1846*	0.0647*	0.0191	-0.0805*	1					
(10) Start-up	0.1365*	0.0336*	0.03	-0.1241*	-0.0698*	-0.0683*	-0.0004	0.0321*	-0.4558*	1				
(11) CVC Partner Reputation	0.0301	0.5107*	-0.006	-0.015	0.0066	-0.1155*	0.0021	-0.0878*	-0.0089	-0.0173	1			
(12) Alliance Partner Reputation	0.0866*	-0.0066	0.4995*	-0.0303	0.0691*	-0.0176	0.2164*	-0.0268	-0.0308	0.0301	-0.0021	1		
(13) Patent stock	0.0413*	0.0540*	0.0978*	0.0079	0.1282*	-0.0082	0.1368*	-0.0891*	0.0483*	-0.0509*	0.0470*	0.0194	1	
(14) Private Firm Status	-0.0081	0.00	-0.1266*	0.0670*	-0.0873*	0.0188	-0.1606*	0.0982*	-0.0001	-0.0078	0.0085	-0.0676*	-0.0215	1

7.2.4 Logit Model

The coefficient estimates from the logit regression are reported in Table 7.5. The effects of control variables on the selection of a target firm are shown in Model 1. The main effect of inter-organisational relationships of firms, that is, CVC investments and alliances, with controls are shown in Model 2. The interaction effects between the two types of inter-organisational relationships and start-up firms are included in Model 3. The interaction effects between the two types of inter-organisational relationships and the reputation indicators (CVC investor listed on the Midas survey and alliance partner listed on Fortune's Most Admired Companies survey) are shown in Model 4. The complete framework is shown in Model 5.

The first model shows that the results of all of the control variables are not statistically significant. The fact that other factors found important in previous research did not predict selection here provides additional evidence that the matching methodology implemented was effective in generating comparable sets of cases and controls, similar even on covariates not explicitly used in the matching process (Rogan and Sorenson, 2014). Profitability as measured by return on assets was used as a pre-treatment variable in the matching process and its coefficient is positive but not statistically significant in all the models. Size as measured by the logarithm of number of employees, was also used as a pre-treatment variable in the matching process and its coefficient is also not statistically significant in all the models. Although other control variables such as liquidity, R&D expenditure, dummy on missing R&D values, patent output and private firm status are not statistically significant in the complete model framework, they were not used as pre-treatment variables in the matching process. Industry and year effects are not statistically significant and were used in the matching process.

In the first hypothesis 1a and 1b, I argued that a firm's inter-organisational relationships, in terms of CVC investments and alliances are positively related to acquisition likelihood. The coefficient of CVC investments (0.482, $p<0.01$) and alliances (0.0967, $p<0.01$)

are positive and significant in model 2 in Table 7.5. Thus, I find support for both hypotheses h1a and h1b.

Table 7.5. Target Selection Model: Results of the logit analysis – probability of being acquired.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Acquisition	Acquisition	Acquisition	Acquisition	Acquisition
CVC Investments		0.482***	0.356***	0.973***	0.814***
		(0.0779)	(0.0702)	(0.131)	(0.137)
Alliances		0.0967***	0.0552*	0.0838***	0.0410
		(0.0242)	(0.0301)	(0.0285)	(0.0350)
Start-up			0.836***		0.866***
			(0.124)		(0.125)
CVC Investments X Start-up			1.572***		1.119**
			(0.459)		(0.473)
Alliances X Start-up			0.188***		0.204***
			(0.0713)		(0.0755)
CVC Partner Reputation				1.695	1.846
				(1.944)	(1.932)
CVC Investments X CVC Partner Reputation				-1.018***	-0.844***
				(0.220)	(0.222)
Alliance Partner Reputation				3.858**	4.962***
				(1.649)	(1.904)
Alliances X Alliance Partner Reputation				-0.234*	-0.327**
				(0.133)	(0.161)
Liquidity (log)	-0.0988	-0.0846	-0.0405	-0.0647	-0.0208
	(0.0622)	(0.0629)	(0.0660)	(0.0638)	(0.0663)
Size (log)	-0.00345	-0.0395	0.0177	-0.0395	0.0169
	(0.0358)	(0.0374)	(0.0387)	(0.0381)	(0.0391)
Profitability	0.00111	0.00274	0.00333	0.00103	0.00175
	(0.00207)	(0.00225)	(0.00235)	(0.00221)	(0.00229)
Patent stock	0.0705	0.00219	0.0653	0.0275	0.0876
	(0.0767)	(0.0817)	(0.0808)	(0.0816)	(0.0805)
R&D Expenditure	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

R&D missing (dummy)	-0.232	-0.155	-0.152	-0.150	-0.148
	(0.141)	(0.147)	(0.149)	(0.149)	(0.151)
Private Firm Status (dummy)	0.325	0.437*	0.306	0.421*	0.289
	(0.225)	(0.238)	(0.238)	(0.241)	(0.242)
Industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	-2.006***	-2.084***	-2.445***	-2.145***	-2.489***
	(0.362)	(0.373)	(0.383)	(0.378)	(0.386)
Observations	3,798	3,798	3,798	3,798	3,798
Total No. of Acquired Firms	477	477	477	477	477
Total No. of Control Firms	1825	1825	1825	1825	1825
Total No. of Firms	2302	2302	2302	2302	2302
Chi^2	6.963	83.02	182.2	132.0	215.0
Pseudo R^2	0.00243***	0.0289***	0.0635***	0.0460***	0.0749***
Log Likelihood	-1432	-1394	-1344	-1369	-1328

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

I also evaluated marginal effects at the means of the independent variables. These are reported in Table A-4 in Appendix A. The results from the marginal effects of CVC investments show that the probability of being acquired would be 5.2 percentage points higher [the marginal effect of CVC investments evaluated at sample means of independent variables (0.0516 X 100)]. The results from the marginal effects of alliances show that the probability of being acquired would be 1.03 percentage points higher [the marginal effect of alliances evaluated at sample means of independent variables (0.0103 X 100)]. With marginal effects at the means, an average is defined as having mean value for the other independent variables in the model (Williams, 2012).

The second hypothesis 2a argued that the interaction between CVC investments and start-ups strengthens the effect of inter-organisational relationships on the firm's likelihood of being acquired. The coefficient of the interaction effect between CVC investments and start-up is positive and significant (1.572, $p<0.01$) in model 3 in Table 7.5. However, the interaction effect cannot be interpreted simply by looking at the sign and statistical significance of the coefficient on the interaction term for a logit model (Ai and Norton, 2003). Like the marginal effect of a single variable, the magnitude of an interaction effect depends on all the covariates in the model (Norton et al., 2004). I explain the interaction effects graphically (Hoetker, 2007). The graphs are attached in Appendix A. Two graphs are plotted – the interaction effects and z-statistics of the interaction effects. In both graphs, the x-axis displays the predicted probabilities. Figure A-1 in Appendix A, displays the interaction effect graph against the predicted probabilities and shows that the interaction effect is positive for some observations and negative for others. The graph on the z-statistics of interaction effects shows the observations at which the interactions are significant. In terms of the significance of the interaction effects (Figure A-2), these are stronger for observations when the interaction effect is positive with z-statistics almost as high as 10. The interaction effects are not statistically significant when the observations of the interaction effects are negative.

To further explore the effect of interaction between CVC investments and start-up, I report the average probability of acquisition likelihood for specific values of CVC investments and start-up. Table A-5 in Appendix A shows that when the value of CVC investment is set to zero, the effect of increasing start-up from its minimum (zero) to maximum (one) increases the average probability of acquisition likelihood by 11.36% (0.211 – 0.0983) and when the value of CVC investment is set to one, the effect of increasing start-up from its minimum (zero) to maximum (one) increases the average probability of acquisition likelihood by 49.55% (0.63 – 0.1345). This increase suggests that the effect of start-up on the probability of acquisition likelihood increases for firms that are engaged in CVC investments.

Hypothesis 2b argued that the interaction between alliances and start-up strengthens the effect on the firm's likelihood of being acquired. The coefficient of the interaction effect between alliances and start-up is positive and significant (0.188, $p<0.01$) in model 3 in Table 7.5. Graphical displays in Appendix A, Figure A-3, of interaction effects show that it is positive for some observations and negative for a few. For firms whose predicted probability of being acquired is 0.2, the interaction effect between alliances and start-up is positive for most observations (Figure A-3). The interaction effects are negative for firms with a predicted probability of acquisition around 0.8 (Figure A-3). The statistical significance of the interaction effect is often stronger for most of the observations when the interaction effect is positive than when negative (Figure A-4). See figures attached in Appendix A.

Further, I explore the effect of interaction between alliances and start-up and report the average probability of acquisition likelihood for specific values of alliances and start-up. Table A-5 included in Appendix A shows that when the value of alliances is set to zero, the effect of increasing start-up from its minimum (zero) to maximum (one) increases the average probability of acquisition likelihood by 11.89% (0.2196 – 0.10066) and when the value of alliances is set to one, the effect of increasing start-up from its minimum (zero) to maximum (one) increases the average probability of acquisition likelihood by 15.71% (0.2629 – 0.1058).

This increase suggests that the effect of start-up on the probability of acquisition likelihood increases for firms that are engaged in alliances.

Hypothesis 3a investigates the interaction between CVC investments and reputation of investor affiliated with a firm. The coefficient of CVC investments is positive and significant. The coefficient of reputation of CVC investor affiliated with a firm is positive but not statistically significant. The coefficient of the interaction effect between CVC investments and reputation of CVC investor affiliated with a firm is negative and significant (-1.018, $p<0.01$) in model 4 in Table 7.5. Figure A-5 in Appendix A, shows that the interaction effect is negative for most of the observations. In terms of the significance of the interaction effects, these are significant for the observations in the sample (Figure A-6).

I explore the effect of interaction between CVC investments and reputation of CVC investor affiliated with a firm listed on the Midas survey and report the average probability of acquisition likelihood at specific values of the two variables. Table A-5 in Appendix A shows that when the value of CVC investments is set to zero, the effect of increasing reputation of CVC investor affiliated with a firm from its minimum (zero) to maximum (one) increases the average probability of acquisition likelihood by 28.3% (0.399 – 0.116) and when the value of CVC investments is set to one, the effect of increasing reputation of CVC investor affiliated with a firm from its minimum (zero) to maximum (one) increases the average probability of acquisition likelihood by 13.4% (0.3888 – 0.2553). This shows that the effect of CVC investments on the probability of acquisition likelihood decreases for firms that are affiliated with a high reputation CVC investor.

Hypothesis 3b tests for the interaction effect between alliances and reputation of alliance partner affiliated with a firm. The coefficient of alliances and the reputation of alliance partner affiliated with a firm are positive and significant. However, the coefficient of the interaction effect between strategic alliance and reputation of alliance partner affiliated with a firm is negative and significant (-0.234, $p<0.1$) in model 4 in Table 7.5. Figure A-7 in Appendix A, shows that the interaction effects[21] are negative for most of the observations. In terms of the significance of interaction effects, these are mostly significant (Figure A-8).

I explore the effect of interaction between alliances and reputation of alliance partner affiliated with a firm listed on the Fortune's Most Admired Companies survey and report the average probability of acquisition likelihood at specific values of the two variables. Table A-5 (see Appendix A) shows that when the value of alliances is set to zero, the effect of increasing reputation of alliance partner affiliated with a firm listed on Fortune's Most Admired Companies survey from its minimum (zero) to maximum (one) increases the average probability of acquisition likelihood by 71.5% (0.836 – 0.121) and when the value of alliances is set to one, the effect of increasing reputation of alliance partner affiliated with a firm listed on Fortune's Most Admired Companies survey from its minimum (zero) to maximum (one) increases the average probability of acquisition likelihood by 68.6% (0.816 – 0.130). This shows that the effect of alliances on the probability of acquisition likelihood decreases for firms that are affiliated with a high reputation alliance partner.

I also conducted robustness checks on the variable for start-up and the reputation indicators. The results from these regressions are included in Table A-6 in Appendix A. At first, I conducted the same regressions using firm age instead of start-up. The coefficient of the interaction effect between CVC investments and firm age is negative and statistically significant (-0.0250, $p<0.1$), which suggests that young firms (of age 7 years or less) that are CVC-backed are more likely of being acquired and old firms with CVC investments are less likely of being acquired. This serves as a confirmation of the interaction effects between CVC investments and start-up. Next, I checked the interaction effects between alliances and firm age

[21] The margins do not provide a separate effect for the interaction. It only provides the marginal effects of the component terms. In my study, I computed the marginal effects at the means. The value of the interaction term cannot change independently of the values of the component terms which makes it difficult to compute a separate effect for the interaction. It is harder to discern the interdependencies between the interaction term itself and the variables used to compute the interaction term. More information can be found in Williams (2012), Stata Journal.

which suggest the existence of negative and significant effect as shown by the coefficient of the interaction effect (-0.00984, $p<0.01$). These results confirm the findings that young firms engaged in alliances are more likely of being acquired. The average predicted probabilities are also computed for each of the interaction effects under investigation and are included in Table A-5 in Appendix A.

Further, robustness checks were carried out on the reputation indicators. Table A-7 in Appendix A displays these results. To do this, I split the variable on the reputation of CVC investors affiliated with a prospective target into the number of CVC investments from investors listed on the Midas list and the number of CVC investments from investors other than the ones listed on Midas survey. The results show that the coefficient is negative and statistically significant which suggests that firms receiving CVC investments from high reputation partners are less likely of being acquired. The coefficient of the number of CVC investments a firm receives when a CVC investor is other than the one listed on the Midas survey is positive and statistically significant. Similarly, the variable on reputation of alliance partner affiliated with a firm is also split into the number of alliances with high reputation alliance partners listed on Fortune's Most Admired Companies (FMAC) survey and the number of alliance partners with firms other than the ones listed on FMAC survey. The results show that the coefficient of the number of alliances of a firm when a high reputation alliance partner is affiliated with it is negative but not statistically significant. In this case, the coefficient is positive and statistically significant when a firm is affiliated with an alliance partner other than the one listed on FMAC list.

7.3 Study 2: Acquired Firm Innovation Performance Results

7.3.1 Target Firm Performance Model: Sample of Acquired Firms

Prior to conducting the analysis, I first identified all the firms that were active and those that dissolved after an acquisition. For each acquired firm, I tracked the firms in FAME and Hoover's Online, using BVD ID as an identifier, for its activity 3 years after an acquisition. This was done to identify firms that remained active and continued to exist as subsidiaries of the acquirers after an acquisition. An acquired firm is coded as dissolved if the firm was no longer listed in the records of the databases. This is similar to prior work in the study by Rogan and Sorenson (2014). Initially, the total number of firms in the sample was 6420 out of which 682 were acquired. After an acquisition, 630 firms continued to exist as active companies in the acquirer's portfolio. These are reported in table 7.6. below.

Table 7.6. Number of active and inactive acquired firms.

Year	No. of Acquired Firms	No. of Active Acquired Firms	No. of Inactive Acquired Firms
2008	123	117	6
2009	43	41	2
2010	65	61	4
2011	60	56	4
2012	73	62	11
2013	94	87	7
2014	68	63	5
2015	97	87	10
2016	59	56	3
Total	682	630	52

7.3.2 Coarsened Exact Matching

Prior to matching, the total number of acquired and non-acquired firms in the sample was 6420 (public and private firms). From these, the total number of acquired firms was 630 and the total number of non-acquired firms was 5790. After matching, the total number of acquired and non-acquired firms in the sample was 3424. From these, the total number of acquired firms was 442 and the total number of non-acquired firms was 2982. The coarsening is based on size of firms as measured by the natural logarithm of number of employees, profitability of firms as measured by the return on assets, 4-digit industry SIC codes, and year of observation. For the variables used in matching, an exact match is obtained on 4-digit industry SIC codes and year of observation. For firm size and profitability, natural breaks in the data are used to create the coarsening as it is a better approach than using fixed bin sizes that disregard the meaningful breaks in the data (Blackwell, 2010). The CEM method selects firms at random without replacement that match the acquired firms on the pre-treatment variables used in matching.

After matching on the pre-treatment variables, that is, 4-digit industry SIC codes, firm size, firm profitability and observation years, it can be seen that the coarsening of the data reduces the mean value and standard deviation of the sample after using the CEM method (Iacus et al., 2009; Blackwell et al., 2010). Firms that drop out are smaller in terms of firm size in certain industries than those that are retained. Table 7.7. displays a comparison of the descriptive statistics of the pre-treatment variables before and after coarsened exact matching. This shows a reduction in the mean and standard deviation of the pre-treatment variables used in matching the treated and the control groups after an application of the CEM algorithm.

Table 7.7. Descriptive statistics of the acquired firm innovation performance model pre-treatment variables before and after CEM.

	Before CEM		After CEM	
Variable	Treated group	Control group	Treated group	Control group
Size (mean)	4.72	4.19	4.62	4.44
Size (std. dev.)	1.60	1.55	1.44	1.11
Profitability (mean)	1.17	4.57	6.47	7.47
Profitability (std. dev.)	34.79	30.75	22.07	16.17

Panel sample obs.	3940	33498	1687	9230
Number of firms	630	5790	442	2982

7.3.3 Descriptive Statistics

The descriptive statistics of the acquired firm's innovation performance model after CEM from the year 2008 – 2016, are displayed in Table 7.8., which includes information on both acquired and non-acquired firms. During the observation period, of the 442 acquired firms, 131 (29.64%) of them are engaged in CVC investments and/or alliances. Firms were engaged in 3416 inter-organisational relationships at the time of acquisition. Firms were involved in 727 CVC investments and 2689 alliances at the time of acquisition. The acquired firms spent on average 3147 million GBP on R&D compared to their industry, size and profitability matched controls that exhibited less R&D input. The acquired firms were granted 4.55 patents per year and the granted patents received 5.89 citations per year when compared with their matched counterparts that show lower output in terms of patents and citations received per patent. On average, each acquired firm had a total of 836 employees (4.62 expressed in logarithm) and profitability (return on assets) of 6.47%, compared to the matched non-acquired firms. The descriptive statistics also suggest that 93% of the acquired firms are private and 7% are public.

The correlations between the variables after applying a matching method are shown in Table 7.9. I constructed the innovation performance measure using patent count and citations received per patent. One could just use the number of patents granted to a firm as an innovation performance measure but using citations received per patent count provides additional information about the quality of output produced. I computed the correlations between the two measures, and these are highly correlated (0.9688, $p<0.05$). This is consistent with the results of Stuart (2000) who found a high positive correlation (above 0.90 in his study) between patents and citations received per patent in the semiconductor industry. Therefore, in my multivariate analyses of target firm innovation performance, I included one innovation output measure at a time in a regression.

Table 7.8. Descriptive statistics of the acquired firm innovation performance model after CEM.

	All Firms		Acquired Firms		Non-Acquired Firms	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Acquired	0.15	0.36	1.00	0.00	0.00	0.00
Time	0.33	0.47	0.42	0.49	0.31	0.46
Private firm status (dummy)	0.95	0.22	0.93	0.25	0.95	0.21
Liquidity (log)	0.32	0.80	0.22	0.81	0.34	0.80
Size	529.47	5129.92	835.93	6106.56	473.46	4928.87
Size (log)	4.47	1.17	4.62	1.44	4.44	1.11
Profitability	7.31	17.22	6.47	22.07	7.47	16.17
CVC Investments	0.07	0.63	0.22	1.06	0.04	0.50
Alliances	0.25	1.36	0.66	2.21	0.17	1.12
R&D Expenditure	1602.08	30502.67	3147.82	48727.86	1319.56	25810.88
R&D missing (dummy)	0.82	0.38	0.80	0.40	0.83	0.38
Patent output	1.58	23.70	4.55	51.90	1.09	13.14
Citation output	1.97	31.10	5.89	69.57	1.43	16.66
Panel Sample Obs.	10,917		1,687		9,230	
No. of Firms	3424		442		2982	

Table 7.9. Correlations of the acquired firm innovation performance model after CEM (panel sample obs. = 10917, no. of acquired firms = 442, no. of control firms = 2982, total no. of firms = 3424). Pairwise correlations show significance at the 5% level and are marked by an asterisk (*).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Acquired	1											
(2) Time	0.0806*	1										
(3) CVC Investments	0.1049*	-0.0216*	1									
(4) Alliances	0.1297*	0.0198*	0.0175*	1								
(5) Size (log)	0.0538*	-0.0019	0.0009	0.1729*	1							
(6) Profitability	-0.0208*	0.0219*	-0.1476*	-0.0268*	0.0335*	1						
(7) Liquidity (log)	-0.0536*	0.0078	-0.0280*	-0.0672*	-0.0591*	0.2670*	1					
(8) R&D Expenditure	0.0217*	0.0181	-0.0029	0.2900*	0.1524*	-0.0054	-0.0326*	1				
(9) R&D missing (dummy)	-0.0286*	-0.0314*	-0.0228*	-0.0405*	-0.1760*	-0.0378*	-0.0825*	-0.1132*	1			
(10) Private firm status (dummy)	-0.0338*	-0.0034	0.0066	-0.1304*	-0.1273*	0.0262*	0.0489*	-0.1481*	0.0984*	1		
(11) Patent output	0.0526*	0.003	0.0098	0.0450*	0.1097*	0.0138	0.0016	0.0755*	-0.0463*	-0.0790*	1	
(12) Citation output	0.0514*	0.0008	0.01	0.0424*	0.1036*	0.0144	-0.0052	0.0650*	-0.0387*	-0.0819*	0.9688*	1

7.3.4 Post-acquisition Innovation Output of Acquired Firms

The study investigates whether and how acquisitions of the target firm with pre-merger inter-organisational relationships affect the innovation output of the acquired firm following the event – the ex post treatment effect. The effect of an acquisition on the innovation performance of acquired firms is estimated through a difference-in-differences regression using a panel data set that contains information on deals in the treatment and control sample from three years prior to an acquisition to three years after an acquisition. A triple differences analysis takes into account the effect of an acquisition on innovation performance post-merger for acquired firms with inter-organisational relationships. The dependent variable, *Patent output*, is the sum of patents of a target firm *i* in each year *t* of observation. The indicator variable, *Time* equals one for the post-acquisition time period and zero otherwise. The indicator variable *Acquired* equals one for the treatment group and zero otherwise (that is, for control group). As a result, the approach is to estimate differences over time in *Patent output* for the same cross-section units (Wooldridge, 2002).

The effect of an acquisition on post-acquisition innovation output is reported in Table 7.10. The first column (1) presents coefficient estimates from the Poisson regression and difference-in-differences analysis. The coefficient of *Acquired* is positive and significant (1.282, $p<0.01$) and captures possible differences between the treatment and control groups in the period before an acquisition. The coefficient of *Time* is positive and significant (0.421, $p<0.01$) at the 1% level, suggesting that the innovation performance is higher in the post-acquisition period for the treatment group and control groups. The coefficient of the interaction term *Acquired X Time* is negative and significant (-0.715, $p<0.01$). This means that the innovation performance, in terms of patent output of acquired firms decreases after an acquisition.

The study investigates the treatment effect of an acquisition on the post-acquisition innovation performance of acquired firms engaged in pre-acquisition inter-organisational relationships. Column (2) presents coefficient estimates from the Poisson regression and the difference-in-difference-in-differences analysis for firms engaged in a particular number of *CVC Investments*. The coefficient of interest is the three-way interaction term, *Acquired X Time X CVC Investments*. This is positive and significant (0.925, $p<0.01$), indicating that acquired firms with at least one CVC investment before an acquisition increased innovation performance after an acquisition than those that did not have CVC investments before an acquisition (relative to potential targets not acquired). Column (3) presents coefficient estimates from the Poisson regression and triple differences analysis for firms engaged in a certain number of *Alliances*. The coefficient of interest is the three-way interaction term, *Acquired X Time X Alliances*. This shows a positive and significant effect (0.0564, $p<0.01$), indicating that acquired firms with at least one alliance before an acquisition increased innovation performance after an acquisition than those that did not have alliances before an acquisition (relative to potential targets not acquired). The DDD estimate starts with time changes in averages for firms with at least one CVC investment (alliance) in the treatment group and then nets out the change in means for firms with at least one CVC investment (alliance) in the control group and the change in means for firms without CVC investment (alliance) in the treatment group (Imbens and Wooldridge, 2007). To facilitate interpretation of the interaction terms, the variables CVC investments and alliances have been centered at the mean following Aiken and West (1996).

The complete model is presented in column (4) and indicates that the three-way interaction term for CVC investments (0.348, $p<0.01$) and alliances (0.0611, $p<0.01$) in the full model shows positive and significant effect, which suggests that acquired firms with at least one CVC investment (alliance) prior to an acquisition increased innovation output after an acquisition, compared to acquired firms that did not have CVC investments (alliances). This shows support for hypotheses 4a and 4b. The post-acquisition innovation output of acquired firms declines (-0.677, $p<0.01$) as a result of the event. The control variables indicate that acquisitions of private firms, larger firms, firms with higher profitability, higher R&D expenditure, greater investment opportunities, and firms with lower financial constraints create more innovations post-acquisition (Seru, 2014).

Table 7.10. Results of the Poisson Estimates of Acquired Firm Innovation Performance – Patent Output.

	(1)	(2)	(3)	(4)
VARIABLES	Patent Output	Patent Output	Patent Output	Patent Output
Acquired	1.282***	1.272***	1.198***	1.182***
	(0.0178)	(0.0178)	(0.0210)	(0.0211)
Time	0.421***	0.380***	0.534***	0.537***
	(0.0178)	(0.0186)	(0.0187)	(0.0194)
Acquired X Time	-0.715***	-0.689***	-0.654***	-0.677***
	(0.0311)	(0.0319)	(0.0338)	(0.0346)
CVC Investments		0.0199		0.0237*
		(0.0130)		(0.0130)
Acquired X CVC Investments		0.145***		0.157***
		(0.0168)		(0.0168)
Time X CVC Investments		-0.544***		0.0111
		(0.0570)		(0.0496)
Acquired X Time X CVC Investments		0.925***		0.348***
		(0.0638)		(0.0570)
Alliances			0.00557*	0.00407
			(0.00308)	(0.00309)
Acquired X Alliances			0.0643***	0.0708***
			(0.00553)	(0.00555)
Time X Alliances			-0.186***	-0.189***
			(0.00837)	(0.00892)
Acquired X Time X Alliances			0.0564***	0.0611***
			(0.0115)	(0.0120)
Liquidity (log)	0.599***	0.598***	0.583***	0.584***
	(0.0110)	(0.0110)	(0.0110)	(0.0110)
Size (log)	1.097***	1.114***	1.107***	1.122***
	(0.00683)	(0.00691)	(0.00689)	(0.00698)
Profitability	0.0189***	0.0192***	0.0192***	0.0200***
	(0.000682)	(0.000685)	(0.000683)	(0.000685)
R&D Expenditure	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D missing (dummy)	-0.459***	-0.442***	-0.433***	-0.426***
	(0.0156)	(0.0157)	(0.0161)	(0.0162)
Private firm status (dummy)	0.0550***	0.0587***	0.0435*	0.0660***
	(0.0213)	(0.0214)	(0.0223)	(0.0225)
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	-5.269***	-5.399***	-5.421***	-5.563***
	(0.0659)	(0.0666)	(0.0662)	(0.0671)
Observations	10,917	10,917	10,917	10,917
No. of Acquired Firms	442	442	442	442
No. of Control Firms	2982	2982	2982	2982
Total No. of Firms	3424	3424	3424	3424
Pseudo R^2	0.404***	0.407***	0.409***	0.412***

Chi^2	76842	77402	77945	78409
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

I estimated a difference-in-differences regression using a different measure on innovation performance, that is, through *Citation output*, which is measured as the sum of citations received by patents of a target firm *i* in each year *t* of observation. The approach is to compare changes over time in novelty of inventions of the target firms within the treatment and control groups prior to and after the event for the same cross-section units (Wooldridge, 2002). The outcome variable is a count; thus, Poisson regression has been used accordingly.

The effect of an acquisition on the post-acquisition innovation performance measured by citation-weighted patent count is reported in Table 7.11. Column (1) presents coefficient estimates of the difference-in-differences analysis, which shows that the coefficient of *Acquired* is positive and significant (1.244, p<0.01) and captures possible differences between the treatment and control groups in the period before an acquisition. The coefficient of *Time* is positive and significant (0.146, p<0.01) at the 1% level, which suggests that the innovation performance is higher in the post-acquisition period for the treatment and control groups. The coefficient of the interaction term, *Acquired X Time* is negative and significant (-0.337, p<0.01), which indicates that an acquisition has a negative effect on the innovation performance of acquired firms, in terms of the quality of output and drops after an acquisition.

The treatment effect of an acquisition on the post-acquisition innovation performance of acquired firms engaged in pre-acquisition inter-organisational relationships is examined next. Column (2) presents coefficient estimates from the Poisson regression and triple differences analysis for firms engaged in a particular number of *CVC Investments*. The coefficient of interest is the three-way interaction term, *Acquired X Time X CVC Investments*. The results indicate a positive and a significant effect (1.503, p<0.01), which suggests that acquired firms with at least one CVC investment before an acquisition increased novelty of innovation after an acquisition than those that did not have CVC investments prior to an acquisition (relative to potential non-acquired firms). Next, coefficient estimates from the Poisson regression and the difference-in-difference-in-differences analysis are obtained on the firms engaged in a particular number of *Alliances*. These are shown in column (3). The coefficient of interest is the three-way interaction term, *Acquired X Time X Alliances*. This is positive and significant (0.0888, $p<0.01$), indicating that acquired firms with at least one alliance pre-acquisition increased innovation output post-acquisition than those that did not have alliances before an acquisition (relative to potential targets not acquired). The variable CVC investments and alliances have been centered at the mean to facilitate interpretation of the interaction terms (Aiken and West, 1996).

In column (4), the full model shows the difference-in-difference-in-differences estimates which suggest that acquired firms with pre-acquisition inter-organisational relationships, that is, CVC investments (0.779, $p<0.01$) and alliances (0.0710, $p<0.01$), produce significantly more important innovations as depicted by an increase in citation output, after an acquisition, compared to acquired firms without inter-organisational relationships. This shows support for the predictions 4a and 4b. The quality of innovation output of acquired firms decreases post-acquisition (-0.184, $p<0.01$). Using a different method of operationalisation on innovation performance also provides validity on the findings. The control variables show that the quality of innovation output increases for larger firms, firms with greater profitability, more R&D expenditure, and better financial and managerial resources after an acquisition.

Table 7.11. Results of the Poisson Estimates of the Acquired Firm Innovation Performance – Citation Output.

	(1)	(2)	(3)	(4)
VARIABLES	Citation Output	Citation Output	Citation Output	Citation Output
Acquired	1.244***	1.237***	1.033***	1.028***
	(0.0159)	(0.0159)	(0.0189)	(0.0190)
Time	0.146***	0.0507***	0.232***	0.186***
	(0.0166)	(0.0190)	(0.0172)	(0.0202)
Acquired X Time	-0.337***	-0.241***	-0.222***	-0.184***
	(0.0273)	(0.0289)	(0.0299)	(0.0319)
CVC Investments		0.0974***		0.0995***
		(0.00587)		(0.00593)
Acquired X CVC Investments		-0.0184		0.00514
		(0.0146)		(0.0142)
Time X CVC Investments		-1.233***		-0.520***
		(0.0819)		(0.0893)
Acquired X Time X CVC Investments		1.503***		0.779***
		(0.0879)		(0.0946)
Alliances			-0.0361***	-0.0368***
			(0.00296)	(0.00297)
Acquired X Alliances			0.111***	0.113***
			(0.00519)	(0.00521)
Time X Alliances			-0.215***	-0.195***
			(0.00924)	(0.00982)
Acquired X Time X Alliances			0.0888***	0.0710***
			(0.0114)	(0.0119)
Liquidity (log)	0.404***	0.397***	0.373***	0.369***
	(0.0102)	(0.0102)	(0.0102)	(0.0102)
Size (log)	1.003***	1.015***	1.032***	1.040***
	(0.00600)	(0.00604)	(0.00604)	(0.00608)
Profitability	0.0239***	0.0236***	0.0245***	0.0248***
	(0.000616)	(0.000618)	(0.000617)	(0.000619)
R&D Expenditure	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D missing (dummy)	-0.521***	-0.495***	-0.453***	-0.440***
	(0.0141)	(0.0141)	(0.0145)	(0.0146)
Private firm status (dummy)	-0.113***	-0.141***	-0.204***	-0.206***
	(0.0188)	(0.0187)	(0.0194)	(0.0194)
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	-4.399***	-4.456***	-4.581***	-4.641***
	(0.0586)	(0.0587)	(0.0586)	(0.0590)
Observations	10,917	10,917	10,917	10,917
No. of Acquired Firms	442	442	442	442
No. of Control Firms	2982	2982	2982	2982
Total No. of Firms	3424	3424	3424	3424

Pseudo R^2	0.383***	0.386***	0.391***	0.393***
Chi^2	87383	88102	89302	89662
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1				

7.4 Study 3: Merged Firm's Innovation Performance Model

7.4.1 Coarsened Exact Matching on Acquiring Firm Sample

Before applying a triple differences approach to analyse post-acquisition innovation performance of merged firms, I made two separate matched samples, one for the acquiring firm and the other for the target firms. For the target firms, I used the same data set used in prior studies. For the acquiring firms, I applied the same CEM method, selecting firms at random without replacement that matched the acquiring firm on size which is measured by the natural logarithm of number of employees, profitability which is measured by the return on assets, 4-digit industry SIC codes and observation years. I obtained an exact match on 4-digit industry SIC codes and observation years and used the natural breaks in the data for firm size and profitability to create the coarsening in the data. The output from the matching process shows the number of observations matched and retained as well as those which are pruned because they were not comparable (Blackwell et al., 2010).

Prior to matching, the total number of acquiring and non-acquiring firms in the sample was 3296. From these, the total number of acquiring firms were 102 and the total number of non-acquiring firms were 3194. After matching, there are a total of 897 acquiring and non-acquiring firms in the sample. From these, the total number of acquiring firms is 81 and the total number of non-acquiring firms is 816. Before running coarsened exact matching in the empirical analysis, 102 different public acquirers carry out at least one acquisition during the sample observation period. The 102 firms with acquisition activity make 248 acquisitions prior to CEM. After CEM in the empirical analysis, 81 public acquirers are retained that carry out at least one acquisition and these 81 acquirers make 208 acquisitions. Table 7.12. shows the sample of acquisitions before and after CEM.

Table 7.12. Yearly distribution of acquisitions before and after CEM in the UK from 2008 – 2016.

	Number of Acquisitions	
Year of observation	Before CEM	After CEM
2008	37	28
2009	24	21
2010	29	24
2011	20	17
2012	25	23
2013	42	36
2014	29	23
2015	29	27
2016	13	9
Total	248	208

Acquirers not matched include (1) BASF (9 acquisitions), (2) 600 Group (1 acquisition), (3) British Telecommunications (2 acquisitions), (4) British Technology (1 acquisition) (5) Consort Medical (3 acquisitions), (6) Feedback (1 acquisition), (7) Fire Testing Technology (1 acquisition), (8) Hikma Pharma (1 acquisition), (9) HSS Hire (1 acquisition), (10) HW Martin (1 acquisition), (11) Impellam (1 acquisition), (12) Kainos (1 acquisition), (13) Kommerling (1 acquisition), (14) Meggitt (1 acquisition), (15) NACB (1 acquisition), (16) Pinnacle Technology (1 acquisition), (17) Quest Global (1 acquisition), (18) Reece (1 acquisition), (19) Sky (3 acquisitions), (20) Smith & Nephew (1 acquisition), (21) Vodafone (7 acquisitions). A common characteristic of the acquiring firms that are unmatched is relatively large firm size (logarithm of number of employees in excess of 11.19) compared to matched acquirers.

7.4.2 Descriptive Statistics

After an application of the CEM method on acquiring firms, the mean value and standard deviation of the sample is reduced due to the coarsening of the data (Iacus, et al., 2009; Blackwell et al., 2010). Table 7.13. shows a comparison of the descriptive statistics of the pre-treatment variables before and after coarsened exact matching on acquiring firms.

Table 7.13. Descriptive statistics of the pre-treatment variables before and after CEM on acquiring firms.

	Before CEM		After CEM	
Variable	Treated group	Control group	Treated group	Control group
Size (mean)	6.14	4.15	5.88	3.73
Size (std. dev.)	2.56	2.51	2.36	2.40
Profitability (mean)	2.63	-6.87	2.08	1.08
Profitability (std. dev.)	20.79	44.58	17.10	17.56
Panel sample obs.	753	18318	372	2112
Number of firms	102	3194	81	816

Table 7.14. shows the descriptive statistics of the acquiring and non-acquiring firms after CEM, during the period 2008 – 2016. The acquiring firms exhibit large firm size, on average 6244 employees, as compared to the industry, profitability and size-matched controls. Acquiring firms have better profitability, return on assets of 2.08%, when compared with the matched non-acquiring controls. On average, acquiring firms spend 20828 million GBP on R&D, are granted 6.60 patents per year and the patents granted receive 1.19 citations per year. This shows relatively low patent output and citation-weighted output compared to the R&D output of the matched non-acquiring firms that had a large patent stock, on average 71.69 patents per year and receive 17.14 citations on patented inventions.

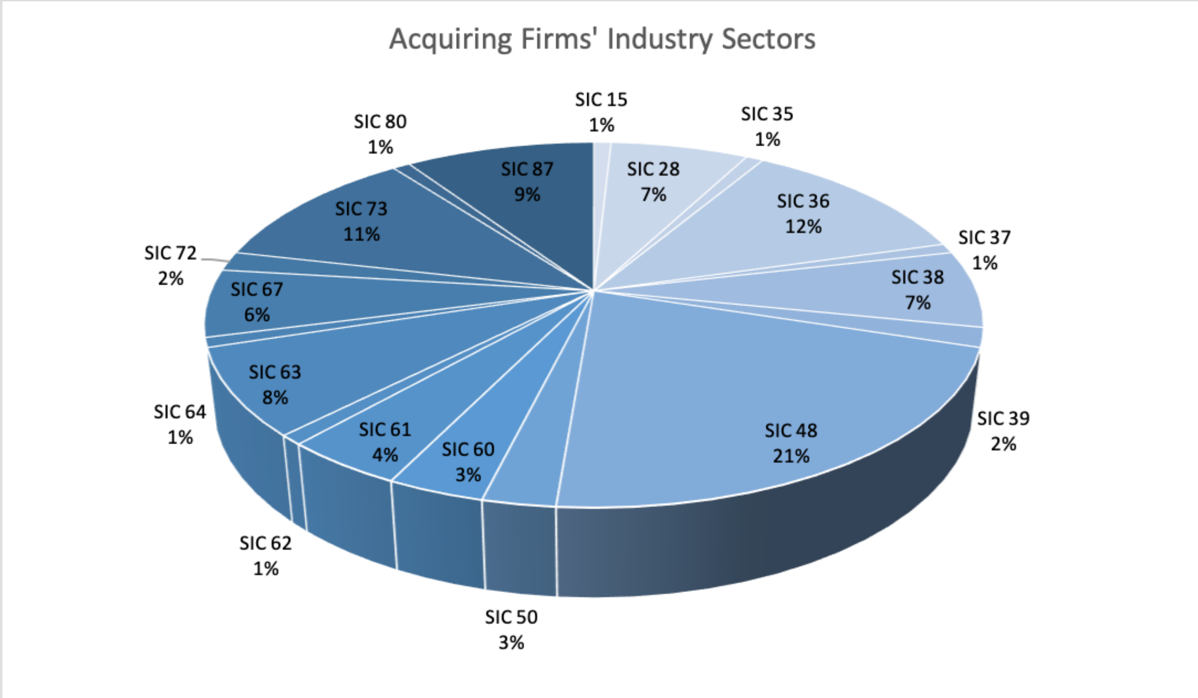
The population of acquiring firms in the high technology and non-high technology industries in the UK are displayed in a pie chart in Figure 7.2. These include 1% in Building Construction (SIC 15), 7% in Chemicals and Allied Products (SIC 28), 1% in Industrial and Commercial Machinery and Computer Equipment (SIC 35), 12% in Electronics and Electrical Equipment (SIC 36), 1% in Transportation Equipment (SIC 37), 7% in Measuring, Analysing and Controlling Instruments; Photographic, Medical and Optical Goods (SIC 38), 2% in

Miscellaneous Manufacturing Industries (SIC 39), 21% in Communications (SIC 48), 3% in Wholesale Trade (SIC 50), 3% in Depository Institutions (SIC 60), 4% in Non-Depository Credit Institutions (SIC 61), 1% in Security and Commodity Brokers, Dealers, Exchanges and Services (SIC 62), 8% in Insurance Carriers (SIC 63), 1% in Insurance Agents, Brokers, and Service (SIC 64), 6% in Holding and Other Investment Offices (SIC 67), 2% in Personal Services (SIC 72), 11% in Business Services (SIC 73), 1% in Health Services (SIC 80), and 9% in Engineering, Accounting, Research, Management and Related Services (SIC 87).

Table 7.14. Descriptive statistics of the acquiring firm sample after CEM.

	All Firms		Acquiring Firms		Non-Acquiring Firms	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Acquiring Firm	0.11	0.31	1.00	0.00	0.00	0.00
Time	0.55	0.50	0.69	0.46	0.53	0.50
Acquirer Size	2781.09	17179.78	6244.91	18485.85	2368.22	16972.29
Acquirer Size (log)	3.96	2.49	5.88	2.36	3.73	2.40
Acquirer Profitability	1.18	17.51	2.08	17.10	1.08	17.56
Acquirer Liquidity	4.88	9.60	2.41	5.88	5.18	9.91
Acquirer R&D Expenditure	2948.43	53705.98	20828.51	138450.50	817.22	30068.55
Acquirer Patents	64.76	807.23	6.60	36.79	71.69	853.64
Acquirer Citations	15.44	198.01	1.19	7.57	17.14	209.40
Panel Sample Obs.	2484		372		2112	
No. of firms	897		81		816	

Figure 7.2. Distribution of High Technology and Non-High Technology Acquiring Firms in the UK.



The descriptive statistics of the merged (acquiring and acquired) firm's innovation performance model are reported in Table 7.15. Of the 208 merged firms, 64 (30.77%) acquired firms are engaged in CVC investments and alliances at the time of acquisition. The merged pairs (acquired and acquiring firms) have on average 6.58 combined patents per year and 2.12 combined citations received per patent in a year. These are relatively less than the combined patent output of the non-merged pairs (non-acquired and non-acquiring firms), that depict on average, 153.43 patents per year. The combined citations received per patents of the non-merged pairs is also higher, on average 27.98 citations, as compared to the merged pairs. The variable *related* accounts for the industry relatedness between the acquirer and target firms, as measured by the same last 4-digit industry SIC codes of the acquirer and targets. This shows that 18% of the acquisitions are related, that is, within the same industry of the acquirer and targets.

The correlation between the variables of the merged firm's innovation performance model are displayed in Table 7.16. The relatively low correlations between the independent variables suggest there is no problem of multicollinearity in the sample. According to prior studies, high correlation exists between the two measures of innovation output – patent and citations received per patent output (Bena and Li, 2014). In my study, I find high correlation between the patent and citation-weighted patent measures (0.9182, $p<0.05$) that are also significant at the 5% level. As a result, one innovation performance measure at a time is included in the regression in the multivariate analyses of the merged firm's innovation output model. There is a positive and significant correlation between CVC investments and alliances of the acquired firms (0.0175, $p<0.05$), which indicates that merged firms are likely to acquire firms with CVC investments and alliances.

Table 7.15. Descriptive statistics of the merged firm's innovation performance model.

	Merged Firms		Non-Merged Firms	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Merged Firms	1	0	0	0
Time	0.44	0.50	0.23	0.42
CVC Investments	0.10	0.42	0.02	0.28
Alliances	0.21	1.06	0.06	0.69
Size	14088.36	22102.78	10328.39	30295.10
Size (log)	7.18	2.76	5.39	3.10
Profitability	2.40	13.81	1.41	19.10
Liquidity	1.83	4.32	3.59	8.01
R&D Expenditure	10665.68	97721.98	2505.86	22507.64
Patent output	6.58	38.20	153.43	829.58
Citation output	2.12	11.71	27.98	174.82
Related	0.18	0.38	0.14	0.34

Table 7.16. Pairwise correlations of the merged firm's innovation performance model. The asterisk (*) indicates significance at the 5% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Merged	1										
(2) Time	0.1646*	1									
(3) Patent output	-0.0573*	-0.0292*	1								
(4) Citation output	-0.0479*	-0.0219*	0.9182*	1							
(5) CVC Investments	0.0862*	-0.0216*	-0.0088	-0.0063	1						
(6) Alliances	0.0630*	0.0198*	-0.0132	-0.0041	0.0175*	1					
(7) Size (log)	0.1758*	0.0376*	0.1147*	0.0744*	0.0099	0.0355*	1				
(8) Profitability	0.0163	0.013	0.0502*	0.0374*	0.0135	-0.0066	0.1040*	1			
(9) Liquidity	-0.0698*	-0.0044	-0.0546*	-0.0483*	-0.0153	-0.0188*	-0.3631*	-0.0471*	1		
(10) R&D Expenditure	0.0654*	0.0054	0.0154	0.0093	0.0025	0.1098*	0.1110*	0.0145	-0.0263*	1	
(11) Related	0.0382*	-0.0649*	-0.0309*	-0.0321*	-0.0065	-0.0248*	0.0303*	0.0484*	-0.1008*	-0.0071	1

7.4.3. Post-acquisition Innovation Output of Merged Firms

The research examines the impact of a merger on post-acquisition innovation output of merged (acquired and acquiring) firms when the acquired firms are engaged in pre-acquisition inter-organisational relationships. A difference-in-differences specification compares the innovation output of merged (acquired and acquiring) firms within the treatment and control group from three years before an acquisition to three years after an acquisition and then compares the difference across the two groups. The triple differences analysis determines the effect of an acquisition on the post-merger innovation performance of merged firms in relation to the pre-acquisition inter-organisational relationships of the acquired firms. The dependent variable, *Patent output*, is the sum of patents of merged firms (acquiring and target firms) *i* in each year *t* of observation. The indicator variable *Time* equals one for the post-acquisition time period and zero for the pre-acquisition time period. The indicator variable *Merged* equals one for treatment group, and zero for control group. As a result, the approach is to estimate the differences over time in innovation performance, measured by the number of patents produced, for the same cross-section units (Wooldridge, 2002).

The results of the DD analysis from the Poisson regression are reported in Table 7.17. In column (1), the coefficient of *Merged* is negative and significant (-2.391, $p<0.01$) and suggests that the patent output is lower in the merged pairs. The coefficient of *Time* is positive and significant (0.0274, $p<0.01$) at the 1% level, which indicates that the innovation output is higher in the post-acquisition period for the treatment and control groups. The coefficient of the interaction term *Merged X Time* is negative and significant (-0.989, $p<0.01$) at the 1% level, and this finding suggests that the combined innovation output declines post-acquisition.

The treatment effect of an acquisition on the post-acquisition innovation performance of merged firms as a function of the pre-acquisition inter-organisational relationships of the acquired firms is estimated through a difference-in-difference-in-differences specification. In this case, the coefficient of interest is the three-way interaction term, *Merged X Time X CVC*

Investments which is presented in column (2). This is negative and significant (-7.508, p<0.01), indicating that the innovation performance of merged firms with at least one CVC investment pre-acquisition decreased innovation performance post-acquisition than those that did not have CVC investments prior to an acquisition (relative to potential non-merged firms). Column (3) presents coefficient estimates from the Poisson regression and triple difference analysis for merged firms whose targets are engaged in a certain number of alliances. The coefficient of interest is the three-way interaction term *Merged X Time X Alliances*. This is negative and significant (-1.749, p<0.01), suggesting that the innovation performance of merged firms with at least one alliance prior to an acquisition decreased innovation performance after an acquisition than those that did not have alliances pre-acquisition (relative to potential non-merged firms). The DDD estimate starts with time changes in averages for firms with at least one CVC investment (alliance) in the treatment group and then nets out the change in means for firms with at least one CVC investment (alliance) in the control group and the change in means for firms without CVC investments (alliances) in the treatment group (Imbens and Wooldridge, 2007). The variables CVC investments and alliances have been centered at the mean following Aiken and West (1996). Therefore, these show the average number of CVC investments and alliances in acquired firms.

The complete model specification, column (4), show the finding on the three-way interaction terms for CVC investments (-7.832, p<0.01) and alliances (-1.699, p<0.01) suggest a considerable fall in the post-acquisition innovation output of merged firms with pre-acquisition inter-organisational relationships in the targets, compared to merged firms whose targets lacked pre-acquisition inter-organisational relationships. It depicts a drop in the combined innovation output of the merged firms after an acquisition (-1.507, p<0.01). Turning to the control variables, it can be seen that the impact on innovation output tends to be significantly better in large and profitable acquiring firms. The post-acquisition innovation output appears to be significantly lower in related acquisitions and imposes significant strain on the acquiring firm’s managerial and financial resources and R&D process.

Table 7.17. Results of the Poisson Estimates of the Merged Firms' Innovation Performance Model – Patent Output.

	(1)	(2)	(3)	(4)
VARIABLES	Patent Output	Patent Output	Patent Output	Patent Output
Merged	-2.391***	-2.557***	-2.393***	-2.553***
	(0.0228)	(0.0226)	(0.0228)	(0.0227)
Time	0.0274***	1.063***	0.0159***	1.051***
	(0.00206)	(0.0193)	(0.00216)	(0.0193)
Merged X Time	-0.989***	-1.893***	-0.563***	-1.507***
	(0.0325)	(0.0383)	(0.0326)	(0.0384)
CVC Investments		2.058***		2.061***
		(0.0154)		(0.0154)
Merged X CVC Investments		1.239***		1.249***
		(0.0605)		(0.0606)
Time X CVC Investments		8.295***		8.292***
		(0.154)		(0.154)
Merged X Time X CVC Investments		-7.508***		-7.832***
		(0.168)		(0.168)
Alliances			0.109***	0.110***
			(0.00313)	(0.00316)
Merged X Alliances			0.225***	0.231***
			(0.0612)	(0.0533)
Time X Alliances			-0.0859***	-0.0875***
			(0.00766)	(0.00768)
Merged X Time X Alliances			-1.749***	-1.699***
			(0.0840)	(0.0786)
Acquiring Firm's Liquidity	-0.472***	-0.421***	-0.462***	-0.413***
	(0.00832)	(0.00798)	(0.00827)	(0.00793)
Acquiring Firm's Size (log)	0.991***	1.023***	0.992***	1.024***
	(0.00348)	(0.00358)	(0.00348)	(0.00357)
Acquiring Firm's Profitability	0.381***	0.389***	0.381***	0.389***
	(0.000983)	(0.00101)	(0.000980)	(0.00100)
Acquiring Firm's R&D	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Related (dummy)	-0.0175***	-0.0170***	-0.0148***	-0.0140***
	(0.00188)	(0.00188)	(0.00189)	(0.00189)
Acquiring Firm's Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	-33.70	-33.17	-33.73	-33.44
	(2,144)	(1,424)	(2,163)	(1,618)
Observations	1,867	1,867	1,867	1,867
No. of Merged Firms	208	208	208	208
No. of Non-merged Firms	1095	1095	1095	1095
Log Likelihood	-163505	-158987	-162091	-157675

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A difference-in-differences regression is estimated using a different metric on innovation performance, *Citation output* which is measured as the sum of citations received by patents of merged firms (acquiring and target firms) *i* in each year *t* of observation. The changes over time are estimated in citation output for the same cross-section units (Wooldridge, 2002). The results from the analysis are displayed in Table 7.18. In column (1), the coefficient of *Merged* is negative and significant (-1.144, p<0.01) depicting a lower level of innovation quality in the treatment group. The coefficient of *Time* is positive and significant (0.0378, p<0.01) at the 1% level, suggesting that the innovation performance is higher in the post-acquisition period for the treatment and control groups. The coefficient of the interaction term *Merged X Time* is negative and significant (-0.687, p<0.01). This means that the innovation performance of merged firms in terms of quality of output produced decreases after an acquisition.

The study estimates the treatment effect of an acquisition on the post-acquisition innovation performance of merged firms in relation to the pre-acquisition inter-organisational relationships of the acquired firms. Column (2) presents the coefficient of interest in the analysis which is the three-way interaction term *Merged X Time X CVC Investments*. This is negative and significant (-8.229, p<0.01), indicating that merged firms with at least one CVC investment before an acquisition reduced innovation performance after an acquisition than those that did not have CVC investments pre-acquisition (relative to potential non-merged firms). The coefficient estimates from the Poisson regression and the triple differences analysis are obtained on the merged firms that acquired firms with alliances. The coefficient of interest is the three-way interaction term *Merged X Time X Alliances*. This is negative and significant (-1.759, p<0.01), indicating that merged firms with at least one alliance pre-acquisition lowered innovation performance post-acquisition than those that did not have alliances before an acquisition (relative to potential non-merged firms). The DDD estimate starts with time changes in averages for firms with at least one alliance in the treatment group and then nets out change in means for firms with at least one alliance in the control group and the change in means for firms without alliances in the treatment group (Imbens and Wooldridge, 2007). The variable CVC investments and alliances have been centered at the mean to facilitate interpretation of the interaction terms (Aiken and West, 1996). Therefore, this shows the average number of CVC investments and alliances in acquired firms.

In the full specification of the model, column (4), indicates that the triple differences estimate on CVC investments (-8.681, $p<0.01$) and alliances (-1.682, $p<0.01$) have a negative and significant effect, which means that merged firms that had acquired firms with pre-acquisition inter-organisational relationships reduced novelty of innovations, following the acquisition, than those that had acquired firms without pre-acquisition inter-organisational relationships. It shows acquisitions led to a decline in the innovation output in terms of the quality of innovations of the combined firms after an acquisition (-1.581, $p<0.01$). In terms of the control variables, the effect on acquisition outcomes are significantly improved in related acquisitions when citation output is used as a measure of innovation performance – as opposed to the negative effect on innovation output when patent output was used as a measure of innovation performance. This acquisition outcome suggests that innovation output improves in terms of quality but not productivity in related acquisitions. With regards to the other characteristics of acquiring firms, the results obtained by using citation output as a measure of innovation performance are similar to the results obtained when innovation output is measured through patent activity to evaluate post-acquisition performance.

7.4.4 Robustness check

I estimated how the post-acquisition innovation performance of acquired firms is affected for the same subsample of 208 deals to clarify the notion of whether the negative effects emerge due to the targets or whether the findings of a negative combined innovation performance should be attributed to the acquiring firm side. These results are reported in Table 7.19 and Table 7.20. The findings suggest that the targets were relatively good performers and their pre-acquisition inter-organisational relationships enabled them to increase innovation growth (both in terms of quantity and quality) post-acquisition compared to acquisitions of targets that lacked pre-acquisition inter-organisational relationships.

Table 7.18. Results of the Poisson Estimates of the Merged Firms' Innovation Performance Model – Citation Output.

	(1)	(2)	(3)	(4)
VARIABLES	Citation Output	Citation Output	Citation Output	Citation Output
Merged	-1.144***	-1.645***	-1.214***	-1.744***
	(0.0361)	(0.0396)	(0.0374)	(0.0405)
Time	0.0378***	1.259***	0.0225***	1.226***
	(0.00481)	(0.0324)	(0.00496)	(0.0323)
Merged X Time	-0.687***	-1.949***	-0.309***	-1.581***
	(0.0513)	(0.0658)	(0.0526)	(0.0667)
CVC Investments		2.536***		2.546***
		(0.0288)		(0.0285)
Merged X CVC Investments		1.485***		1.690***
		(0.0844)		(0.0846)
Time X CVC Investments		9.821***		9.694***
		(0.258)		(0.256)
Merged X Time X CVC Investments		-8.229***		-8.681***
		(0.247)		(0.247)
Alliances			0.168***	0.189***
			(0.00410)	(0.00432)
Merged X Alliances			-0.000131	0.145***
			(0.0525)	(0.0442)
Time X Alliances			-0.115***	-0.134***
			(0.0159)	(0.0159)
Merged X Time X Alliances			-1.759***	-1.682***
			(0.126)	(0.123)
Acquiring Firm's Liquidity	-1.695***	-1.236***	-1.650***	-1.185***
	(0.0247)	(0.0244)	(0.0248)	(0.0241)
Acquiring Firm's Size (log)	0.691***	0.773***	0.696***	0.780***
	(0.00605)	(0.00667)	(0.00606)	(0.00668)
Acquiring Firm's Profitability	0.226***	0.256***	0.227***	0.256***
	(0.00171)	(0.00191)	(0.00170)	(0.00189)
Acquiring Firm's R&D	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Related (dummy)	0.0240***	0.0269***	0.0321***	0.0373***
	(0.00408)	(0.00408)	(0.00411)	(0.00411)
Acquiring Firm's Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	-24.71	-27.36	-25.83	-26.61
	(1,099)	(2,043)	(1,796)	(1,335)
Observations	1,867	1,867	1,867	1,867
No. of Merged Firms	208	208	208	208
No. of Non-merged Firms	1095	1095	1095	1095
Log Likelihood	-68741	-64563	-67724	-63584

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7.19. Results of the Poisson Estimates of the Acquired Firms that are combined with the Acquiring Firms in the Merged Firm's Innovation Performance Model – Patent Output (Target Side).

	(1)	(2)	(3)	(4)
VARIABLES	Patent Output	Patent Output	Patent Output	Patent Output
Acquired	0.176***	0.132***	0.547***	0.492***
	(0.0439)	(0.0446)	(0.0477)	(0.0487)
Time	-0.0537	-0.00631	0.154***	0.201***
	(0.0347)	(0.0348)	(0.0372)	(0.0373)
Acquired X Time	0.518***	0.0506	0.240***	-0.306***
	(0.0682)	(0.0778)	(0.0720)	(0.0844)
CVC Investments		0.243***		0.306***
		(0.0178)		(0.0165)
Acquired X CVC Investments		-0.162***		-0.191***
		(0.0274)		(0.0270)
Time X CVC Investments		0.606***		0.562***
		(0.0432)		(0.0429)
Acquired X Time X CVC Investments		0.567***		0.678***
		(0.0761)		(0.0806)
Alliances			0.154***	0.160***
			(0.00327)	(0.00335)
Acquired X Alliances			-0.122***	-0.114***
			(0.0186)	(0.0185)
Time X Alliances			-0.0112	-0.0117
			(0.0130)	(0.0131)
Acquired X Time X Alliances			0.0494	0.115***
			(0.0391)	(0.0404)
Acquired Firm’s Liquidity (log)	0.269***	0.264***	0.318***	0.311***
	(0.0199)	(0.0200)	(0.0204)	(0.0204)
Acquired Firm’s Size (log)	0.655***	0.666***	0.456***	0.461***
	(0.0117)	(0.0119)	(0.0136)	(0.0139)
Acquired Firm’s Profitability	0.0262***	0.0283***	0.0241***	0.0262***
	(0.00113)	(0.00113)	(0.00114)	(0.00113)
Acquired Firm’s R&D Expenditure	-0.000	-0.000	0.000*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Acquired Firm’s R&D missing (dummy)	-1.093***	-1.051***	-1.127***	-1.056***
	(0.0289)	(0.0291)	(0.0298)	(0.0301)
Acquired Firm’s Private firm status (dummy)	-0.244***	-0.286***	0.126***	0.130***
	(0.0389)	(0.0390)	(0.0408)	(0.0412)
Related	0.244***	0.133***	0.478***	0.390***
	(0.0274)	(0.0281)	(0.0280)	(0.0285)
Acquired Firm’s Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	-3.649***	-3.636***	-3.100***	-3.147***
	(0.119)	(0.119)	(0.121)	(0.122)
Observations	5,593	5,593	5,593	5,593

No. of Acquired Firms	208	208	208	208
No. of Non-acquired Firms	1095	1095	1095	1095
Pseudo R^2	0.207***	0.221***	0.251***	0.267***
Chi^2	10346	11034	12537	13319
Log Likelihood	-19773	-19429	-18678	-18287
Standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Table 7.20. Results of the Poisson Estimates of the Acquired Firms that are combined with the Acquiring Firms in the Merged Firm's Innovation Performance Model – Citation Output (Target Side).

	(1)	(2)	(3)	(4)
VARIABLES	Citation Output	Citation Output	Citation Output	Citation Output
Acquired	-0.145***	-0.219***	0.0366	-0.0437
	(0.0405)	(0.0416)	(0.0436)	(0.0450)
Time	-0.361***	-0.326***	-0.209***	-0.174***
	(0.0320)	(0.0324)	(0.0331)	(0.0335)
Acquired X Time	0.743***	0.301***	0.594***	0.0631
	(0.0642)	(0.0734)	(0.0673)	(0.0794)
CVC Investments		0.404***		0.430***
		(0.00947)		(0.00937)
Acquired X CVC Investments		-0.239***		-0.238***
		(0.0197)		(0.0200)
Time X CVC Investments		0.195***		0.160**
		(0.0676)		(0.0668)
Acquired X Time X CVC Investments		0.932***		1.056***
		(0.0864)		(0.0882)
Alliances			0.0932***	0.103***
			(0.00279)	(0.00286)
Acquired X Alliances			-0.0516***	-0.0399**
			(0.0169)	(0.0169)
Time X Alliances			-0.0950***	-0.0950***
			(0.0144)	(0.0145)
Acquired X Time X Alliances			0.0730**	0.157***
			(0.0330)	(0.0335)
Acquired Firm's Liquidity (log)	0.0129	-0.0193	0.0249	-0.00488
	(0.0169)	(0.0169)	(0.0171)	(0.0172)
Acquired Firm's Size (log)	0.685***	0.708***	0.575***	0.591***
	(0.00997)	(0.0102)	(0.0110)	(0.0113)
Acquired Firm's Profitability	0.0299***	0.0341***	0.0282***	0.0327***
	(0.000989)	(0.000970)	(0.000989)	(0.000967)
Acquired Firm's R&D Expenditure	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Acquired Firm's R&D missing (dummy)	-0.554***	-0.500***	-0.579***	-0.507***
	(0.0230)	(0.0233)	(0.0235)	(0.0239)

Acquired Firm's Private Firm Status (dummy)	0.236***	0.171***	0.528***	0.520***
	(0.0368)	(0.0372)	(0.0387)	(0.0395)
Related	0.140***	0.0289	0.231***	0.143***
	(0.0238)	(0.0244)	(0.0241)	(0.0247)
Acquired Firm's Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Constant	-3.816***	-3.873***	-3.522***	-3.633***
	(0.100)	(0.101)	(0.101)	(0.101)
Observations	5,593	5,593	5,593	5,593
No. of Acquired Firms	208	208	208	208
No. of Non-acquired Firms	1095	1095	1095	1095
Pseudo R^2	0.183***	0.205***	0.199***	0.224***
Chi^2	11945	13430	12999	14655
Log Likelihood	-26745	-26003	-26218	-25390

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

CHAPTER 8

DISCUSSION

8.1 Introduction

This dissertation contributes to our understanding of the role of inter-organisational relationships on choice of takeover targets and explores whether and how such relationships affect post-acquisition innovation outcomes for the acquired and merging firms. The findings of the research show support for some theoretical hypotheses and point towards some shortcomings which can be addressed in future work on the topic. The study takes into consideration the characteristics of acquired and acquiring firms that play a significant role in explaining the variation in acquisition outcomes. Pre-acquisition inter-organisational relationships are a rare event and the ad hoc dataset constructed for these analyses on UK firms illustrates this. The study takes a case-control research methodology to account for selection biases and then evaluates acquisition probability through a logit model. To estimate the cause of the effect, the research combines the method employed to correct for selection biases with a difference-in-differences design. The identification approach relies on a triple differences analyses that enables to observe the influence of pre-acquisition inter-organisational relationships on the post-acquisition innovation outcomes of the acquired and combined firms.

To summarise, the first study finds support that targets with inter-organisational relationships experience higher likelihood of being acquired and show support for hypotheses 1a and 1b. I find that both CVC investments and alliance relationships signal quality of firms to the acquirers. Therefore, I find general support for a 'signalling effect' of inter-organisational relationships of firms and that such relationships are likely to attract acquirers in the M&A market. The moderating condition of a firm being a start-up suggests that firms engaged in inter-organisational relationships are more likely of being acquired. This shows support for the hypotheses 2a and 2b. My study finds that having CVC investments and alliances in start-up firms strengthen the likelihood of acquisition. This is consistent with the explanation that the inter-organisational relationships of start-up firms are more likely to emit positive signals in the M&A market. This reiterates the 'signalling effect' of inter-organisational relationships on the likelihood of acquisition of firms in the early stages of their life cycles. However, the research does not find support for the prediction that an interaction between inter-organisational relationships and affiliations with high reputation CVC investors and alliance partners increases likelihood of being acquired. The results suggest that for firms engaged in inter-organisational partnerships, affiliations with high reputation CVC investors and alliance partners tends to decrease acquisition likelihood. Thus, hypotheses 3a and 3b are not supported by the findings.

The second study sheds light on the impact of pre-acquisition inter-organisational relationships on post-acquisition innovation performance of acquired firms. I find that targets with inter-organisational relationships tend to do better post-deal in terms of innovation output as measured by patent and citations indicators, relative to their counterparts. Thus, I find support for the hypotheses 4a and 4b. This finding provides confirmation of the 'signalling effect' of target inter-organisational relationships and shows that pre-acquisition inter-organisational relationships of targets enable managers to better evaluate potential acquisition targets and to acquire relatively more innovative firms. However, in the third study, the performance of combined firms deteriorates and fails to materialise synergies which highlights a seeming paradox regarding the impact of inter-organisational relationships on the post-acquisition innovation performance. This shows support for the hypotheses 6a and 6b. The present work has some research and managerial implications and proposes promising directions for future research. This chapter establishes a link between the theoretical framework and empirical findings and expands on the contribution to the literature and methods used in this study. A summary of hypotheses is displayed in Table 8.1.

Table 8.1. Summary of Hypotheses

Hypothesis		Support
1a	Firms receiving CVC investments are more likely to get acquired	Yes
1b	Firms engaged in alliances are more likely to get acquired.	Yes
2a	The effect of receiving CVC investments on the likelihood of being acquired is stronger for start-up firms.	Yes
2b	The effect of engaging in alliances on the likelihood of being acquired is stronger for start-up firms.	Yes
3a	The reputation of a CVC investor affiliated with a firm strengthens the effect of receiving CVC investments on the likelihood of being acquired.	No
3b	The reputation of an alliance partner affiliated with a firm strengthens the effect of engaging in alliances on the likelihood of being acquired.	No
4a	The effect of an acquisition on post-acquisition innovation output is positively related to the number of pre-acquisition CVC investments in a target firm.	Yes
4b	The effect of an acquisition on post-acquisition innovation output is positively related to the number of pre-acquisition alliances in a target firm.	Yes
5a	The effect of an acquisition on post-acquisition innovation output of merged firms is positively related to the number of pre-acquisition CVC investments in an acquired firm.	No
5b	The effect of an acquisition on post-acquisition innovation output of merged firms is positively related to the number of pre-acquisition alliances of an acquired firm.	No
6a	The effect of an acquisition on post-acquisition innovation output of merged firms is negatively related to the number of pre-acquisition CVC investments in an acquired firm.	Yes
6b	The effect of an acquisition on post-acquisition innovation output of merged firms is negatively related to the number of pre-acquisition alliances of an acquired firm.	Yes

8.2 Theoretical Insights

The research contributes to the literature on mergers and acquisitions by analysing the influence of inter-organisational relationships of firms on the likelihood of being acquired. The empirical findings are consistent with the view that inter-organisational relationships of firms are taken as signals of firm quality by the acquirers and provide evidence on the determinants of acquisition likelihood. Firms engaged in CVC investments and alliances, are preferred by acquirers as they provide better access to information and help reduce information asymmetry. Additionally, my study builds on Mazzola's et al (2016) view of inter-organisational relationships as signals by bringing in and unpacking the differences between CVC investments and alliances and how their differences influence the preferences of acquirers. It highlights the view that acquirers tend to favour targets with arm's length ties, such as, CVC investments due to the lower interdependence between partners, as compared to taking over firms engaged in alliances that depict 'close relationships' and greater interdependence between connected firms. This not only brings forward the role of the different types of inter-organisational relationships under investigation but also the underlying differences such relationships introduce into the perceptions of acquirers searching to takeover targets. In fact, the analyses also estimate the marginal effects at the means of the independent variables and these show higher marginal effects of the CVC investments on the likelihood of being acquired, 5.2 percentage points, compared to alliances, 1.03 percentage points. This offers further evidence that CVC investments are pursued with the objective of exiting at some stage due to which the propensity to takeover firms with CVC investments is higher compared to firms having alliances.

Moreover, the research contributes to the existing body of research on M&A through the finding that the 'visibility-enhancing effect' of inter-organisational relationships on acquisition likelihood is strengthened for start-up firms. This finding contributes to the view that the objective of CVC investments is to exit the venture at some stage which facilitates acquisition of the target's shares. The results on acquisition of start-up firms with alliances are also consistent with the study by Baum and Silverman (2004) who suggest that young firms engaged in alliances are likely to be seen as signals of firm quality. Therefore, firms having CVC investments and alliances are perceived as signals of firm quality by the acquirers and positively influence the choice of acquirers to speed up the acquisition process of start-up firms.

Contrary to my prediction, I find that affiliations with high reputation partners weaken the effect of inter-organisational relationships on the firm's likelihood of being acquired. Prior literature suggests that affiliations with high reputation partners often undermine the bargaining power of the focal firm and restrict its capacity to appropriate value from the value co-created through such collaborations (e.g. Lavie, 2007; Ozmel et al., 2017). Thus, the results can reflect perspective acquirers' aversion towards firms which are engaged in unbalanced relationships with high status partners. This provides additional evidence as to why the coefficient of alliances becomes insignificant although it is positive in the complete model specification (Table 7.5). Another possibility is that the affiliations of firms with high reputation CVC partners also causes a hike in the acquisition premium (Reuer and Ragozzino, 2012) and the acquirers might not be eager to pay the rising premium on such acquisitions which decreases acquisition likelihood. The results overall indicate that the inter-organisational partnerships of firms explain acquisition likelihood over and above the control variables included on financial and innovation performance characteristics of firms which are not statistically significant in the framework.

Existing research on inter-organisational relationships considered their benefits either collectively or examined CVC investments and alliances in isolation from each other. The literature sheds light on advantages such as resource access, information sharing and investment decisions that both CVC investments and alliances might add. Lately, this research stream has advanced by framing the decision to acquire in explicitly comparative terms and quite a few studies used either real options or information asymmetry (Zaheer et al., 2010; Tong and Li, 2010) to understand when firms use CVC investments or alliances. The value of bringing inter-organisational relationships to the literature on mergers and acquisitions becomes more apparent once signalling theory and interdependencies across the various types of inter-organisational relationships, that is, CVC investments versus alliances are considered. In my research, I explore some of the contingencies that shape the value of signals in the context of M&A market. Even fewer studies have used information economics to attend to the ex-ante exchange hazards that can arise due to asymmetric information in acquisition deals that inter-organisational relationships can help alleviate. I attempt to extend this stream of research by investigating the impact of signals that can overcome adverse selection and thereby facilitate acquirer's choice of target firm. I further unlock the synergetic potential of such signals to create new value in acquisitions.

This work uncovers a unique source of synergy – corporate connections of the firms – that drives acquisitions of firms and brings acquired firms up to speed at innovation post-acquisition. Acquired firms with a mixture of arm's length relationships and close ties in their networks allows them to develop increased adaptive capacity as close ties facilitate learning, coordination and resource pooling (Uzzi, 1996). On the other hand, arm's length ties prevent redundant network links to potentially allow new information inflows for innovation to flourish. This research finds a positive treatment effect of an acquisition on post-acquisition innovation output when there are pre-acquisition inter-organisational relationships in the targets compared to targets without pre-acquisition inter-organisational relationships. The study measures innovation performance by two means: (1) patent output which reveals information about quantity of output produced after an acquisition, and (2) citation output which provides information about quality of output produced post-acquisition. The findings show that the post-acquisition innovation output of acquired firms increases, that is, after an acquisition there is an increase in the number of patents produced by acquired firms with valuable signals than targets not engaged in pre-acquisition inter-organisational relationships. The results on citation output indicate that post-acquisition there is an increase in the quality of output produced by acquired firms with inter-organisational relationships than acquired firms that did not have pre-acquisition inter-organisational relationships. This finding suggests that the two different operationalizations of innovation performance correlate in the same way with post-acquisition outcomes and adds support to the validity of the operationalizations. The acquired firms' inter-organisational business ties in the form of corporate venture capital investments and alliances affect innovation outcomes positively and significantly increase innovation growth.

Consistent with value creation – the results conclude that synergies are derived through a combination of the innovation capabilities of acquired firms and the operations of their connections to realise increased potential value following an acquisition. Thus, corporate venture capital investments and alliances of firms provide an important mechanism to substantially mitigate information asymmetry and adverse selection risk, and enhance innovation performance of acquired firms post-acquisition via their operational synergies.

The study by Graebner (2004) found that most of the value materialised in acquisitions was serendipitous and unforeseen at the time of acquisition and that firms differed to a great extent in their ability to create serendipitous value. In order for merged firms to gain the most from acquisitions of firms with inter-organisational relationships, they must possess the ability to combine their innovation activities with those of the partner in novel ways to generate value. This includes making important decisions on the resources to transfer, retain or divest (Capron et al., 1999). Relevant to my study, this would entail decisions on relationships that need to be retained, forged or terminated and to conduct these decisions effectively. This presents a challenge to the management of merged firms. To achieve new synergetic or innovative combinations, firms would need to combine their existing activities with the newly acquired firms and their inter-organisational relationships – which constitutes an important dynamic capability. In a similar research, Zollo and Singh (2004) explain that the outcomes that are realised from an acquisition are influenced by the degree to which the acquiring firm is able to develop specific capabilities to manage the process of an acquisition. In my research, the focus is on the extent to which the acquired firms' innovation output created through engagement in inter-organisational relationships is combined with the existing innovation activities of the acquiring firms. The extent to which the value potential of the inter-organisational relationships becomes realised depends on the ability of the acquiring firm to manage the expanded network, discover and conduct productive innovation combinations (Wiklund and Shepherd, 2009).

An exploration of the issue of whether and how pre-acquisition inter-organisational relationships of target firms in merged firms facilitate realisation of synergistic gains shows negative and significant effect of an acquisition on the innovation outcomes after an acquisition. Specifically, I proposed and empirically tested whether the innovation performance measures, patent and citation output will be significantly higher in merged firms with pre-acquisition inter-organisational relationships in the targets than those acquired without pre-acquisition inter-organisational relationships. The innovation performance measures, patent and citation output, both indicate negative and significant impact of on acquisition on post-acquisition innovation outcomes in merged firms whose acquired firms are engaged in pre-acquisition inter-firm partnerships compared to targets not involved in pre-acquisition inter-organisational relationships. Both the measures on innovation output correlate in a similar fashion with the outcomes on acquisition effect and provide support on the validity of the findings. The results indicate that it becomes increasingly challenging for firms to manage and integrate the newly acquired firms and its acquired relationships. A substantial amount of the management's time, energy and efforts are dedicated to integrating the acquired firm along (Wiklund and Shepherd, 2009) with its inter-organisational relationships, and diverts managerial attention away from more productive innovation activities which causes a decline in post-acquisition innovation growth. Consequently, while inter-organisational relationships may provide valuable signals of firm quality, lower information asymmetry and reduce the risk of adverse selection, they decrease the realised value for the merged firms because of greater challenges and higher costs involved in integrating the acquired firms and its connections. It is also possible that acquirers are on a declining innovation trajectory and try to offset it through acquisition of promising targets. This could also be an endogeneity issue – that is, the decision to acquire is endogenous to acquirer innovation performance prospects.

8.3 Methodological Insights

This research addresses the question of whether inter-organisational relationships such as CVC investments and alliances influence acquisition likelihood and their impact on innovation outcomes after an acquisition. To examine the research questions of this study, it takes a robust methodological approach called coarsened exact matching and logit regression to estimate acquisition probabilities. It then combines the difference-in-difference-in-differences approach with coarsened exact matching method to yield accurate estimates of the effect of pre-acquisition inter-organisational relationships of firms on post-acquisition innovation outcomes.

In the first set of analyses evaluating probability of an acquisition, the empirical strategy is to create appropriate comparison sets of acquired and non-acquired firms on the basis of observational characteristics of firms associated with the likelihood of being acquired. Building on prior literatures in management and finance which argue that the 'high-performing' firms are more likely of being acquired as they are a good match for appropriate acquirers, I control for profitability operationalised as return on total assets (Bena and Li., 2014). Other observable characteristics of firms used in matching are size of firms (measured by number of employees) and 4-digit industry SIC codes to account for factors correlated with the outcome. Empirically, matching the acquired firms with non-acquired firms on the basis of prior performance strengthens the signalling argument since performance due to resources has already been accounted for in the empirical analysis. Therefore, the method reduces selection bias, generates suitable sets of comparison for treated and control units and the application of a logit regression gives accurate estimates on the likelihood of an acquisition.

Following the difference-in-differences approach with a combination of coarsened exact matching method, the models assessing innovation performance accurately depict the effect of an acquisition. The coarsened exact matching method enhances the overall quality of the treatment and comparison groups by controlling and reducing selection biases. The estimator in the DD analyses then accounts for change in innovation output of the treatment group after an acquisition. To account for the potential effects of pre-acquisition inter-organisational relationships, a third difference is included in the model to evaluate innovation output. This includes the count of the number of CVC investments (alliances) of each target pre-acquisition as well as the interactions of this variable with the other difference-in-differences terms. In the second study, the triple differences method explains that acquired firms with inter-organisational relationships have a positive impact on post-acquisition innovation performance compared to acquired firms that lacked interorganisational relationships. As the variable on inter-organisational relationships is a count variable, it has been centered at the means to facilitate interpretation of the findings (Aiken and West, 1996). My findings provide confirmation that the 'signalling effects' of CVC investments and alliance relationships of targets worked as depicted by a stronger positive influence on the post-acquisition innovation output of acquired firms. This means that target inter-organisational relationships are beneficial to managers of the acquiring firms to identify 'good quality' takeover targets, improve selection and pick more innovative targets.

In the third study, a matched sample on acquiring firms is generated using coarsened exact matching. This accounts for possible selection biases that may arise due to acquiring firm characteristics that can be correlated with the innovation outcomes after an acquisition. For an actual acquisition that did occur, the sample of matched acquirers is combined with the matched sample of targets to generate combinations of deals that could potentially have occurred. This allows to evaluate innovation performance for actual deals that did happen and the performance consequent on counterfactual deals (combinations of deals that could have happened but that did not). A triple differences approach indicates that acquired firms with inter-organisational relationships in the merged firms pre-acquisition affect innovation output after an acquisition than those that did not exhibit inter-organisational relationships pre-acquisition in the merged pairs. I find a negative effect of the relationships of the targets on the combined firms' performance. Although this means that synergies do not materialize, but the positive effect on the target side shows that the 'signalling effect' worked. Targets with relationships increase innovation performance after an acquisition which serves as an indicator of a 'good signal' but the poor performance on the acquirer's side directs towards difficulties arising in integrating acquired firms and their relationships. Although treatment effect methods are well-established in medical science and social sciences, only a few management science or finance studies on mergers and acquisitions have implemented this methodology (for example, see Rogan and Sorenson, 2014; Bena and Li, 2014; Seru, 2014). Even though the treatment effect method does not completely eliminate bias (Bertrand et al., 2004) it reduces the selection bias to accurately estimate the causal effect.

The findings of this study are based on an original database compiled by integrating financial information, mergers and acquisitions, corporate venture capital investments, alliances, patent and citations data and reputation indicators from surveys in magazines. In addition, the study employs state-of the-art empirical strategy on the unique database constructed to enhance the scholars' ability to observe the impact of pre-acquisition inter-organisational relationships as an important impetus in mergers and acquisitions.

CHAPTER 9

CONCLUSION

9.1 Introduction

The key contributions of this dissertation are as follows: using a large and unique dataset over the period 2008 – 2016, the focus is on the role of inter-organisational relationships as signals in pre-acquisition stage and their impact on acquisitions in the post-acquisition stage. I test the significance of signalling theory in the context of firm acquisitions. The signalling theory suggests that in the presence of information asymmetries between two parties, information can be exchanged through signals that indicate characteristics which are costly and difficult to imitate (Spence, 1973, 2002). Acquisitions provide a suitable setting for the theory to be tested because information asymmetries are a feature of the M&A market and restricts the acquirer's selection of target firms. By testing the signalling theory, the research enhances the explanatory power of the information economics views of acquisitions. The research offers compelling insights on the differences between the two types of inter-organisational relationships examined and the differences in the acquirer's perceptions.

In addition, this research work identifies a specific source of synergy – the value of signals – that drives acquisitions of firms engaged in prior relationships and has a positive impact on acquisition outcomes of acquired firms compared to acquired firms that lacked such partnerships. Furthermore, although such signals are effective in overcoming information asymmetries and adverse selection risk, they decrease innovation performance of combined (acquired and acquiring) firms. The difficulties in materialising potential value from acquisitions are conjectured to emerge from the high costs of integrating takeover targets along with their inter-organisational relationships into the acquiring firms'. This diverts the acquirer's attention away from investing in more profitable and innovation-oriented projects towards managing the large network. Another explanation of the findings suggest that the connected targets increase post-acquisition innovation performance which confirms that the signal was effective, but the acquirers tend to perform rather poorly. It is thus possible that acquirers are firms on a declining innovation trajectory, and this is why they choose to carry out acquisitions of targets with a high innovation potential as signalled by their inter-organisational relationships.

9.2 Limitations and Suggestions for Future Research

Like almost all empirical research, this study too has important limitations. First, it does not take into account hostile bids and defence mechanisms employed by firms which might affect acquisition likelihood (Morck, Shleifer and Vishny, 1988). Second, it does not control for acquirer characteristics in the acquisition likelihood model which might also influence likelihood of being acquired. Acquirers essentially drive the decision to select a partner firm, with acquired firms playing a more passive role, by either accepting or rejecting a bid. Rogan and Sorenson (2014) model this as a conditional logit model by controlling acquiring firm characteristics and future research could investigate this further. A different method of operationalization of the variable on reputation of CVC investor and alliance partners affiliated with a firm can offer a more comprehensive understanding of the signal of firm quality. This research has only begun to view some of the conditions under which the relationship between the signals and acquisitions would hold and future research could extend this work.

The research is relevant to acquisitions of high technology firms and patents and citations data are a meaningful measure of innovation in these industries (Cloodt et al., 2006). My sample of acquiring firms is based on all industry sectors in the UK and patent and citations data might not provide an accurate measure of performance post-acquisition for industries other than the high technology sector. It would be worthwhile to examine performance following an acquisition through other indicators such as new product introductions which would be able to capture possible differences in performance for a broad range of industries. This would also enable to capture the effect for firms that do not patent due to secrecy reasons to protect their inventions from getting imitated. Even though the research looks into sources of innovation that originate from both innovation input and output, it would be interesting to take into account a more holistic approach by including additional measures on innovation such as R&D intensity, R&D productivity such as that done in Desyllas and Hughes (2010).

Additionally, a qualitative study would provide richer insights into how acquirer's select targets and manage the post-acquisition integration process. Interviews with the managers of the acquiring and acquired firms would capture possible differences in the management decisions of both firms and how value is created through such acquisitions. The current sample for the study was constructed with the objective of analysing the influence of the inter-organisational relationships of the targets and does not take into account the inter-organisational relationships of the acquiring firms. It is possible that acquiring firm's too have inter-organisational relationships and some of the relationships between the acquiring and acquired firms might even be overlapping. The present study was unable to take into consideration the acquiring firm's relationships due to the severe difficulties encountered in getting access to the database on alliances. However, this can be considered in future research work. The findings of the study suggest that the post-acquisition innovation performance of the acquired firm increases, but the performance of the combined firm decreases. This suggests a possibility of the acquirers being on a downward innovation trajectory and future research work can explore this issue further. Another one of the limitations of my study is that the alliance data included in the thesis comprises of both upstream and downstream alliances. The current study does not look into different types of alliances that influence target firm selection, valuation and performance after an acquisition. For example, work by Porrini (2004) has viewed how different types of alliances, such as, R&D, technology transfer, manufacturing and marketing, and licensing alliances affect post-acquisition performance outcomes. A firm's downstream alliances such as distribution channels, marketing and production facilities are useful for successful product development and commercialization. Upstream alliances indicate patenting of new products and processes which serve as a promising signal of firm quality (Baum and Silverman, 2004). Currently, it is difficult to discern the effect of upstream and downstream alliances on post-acquisition innovation performance. The alliance variable can be split into upstream and downstream alliances and provides a promising area for future research work. Lastly, it would also be interesting for future research to explore whether the performance of combined (acquiring and acquired) firms differs depending on the way the target was integrated. Jemison and Sitkin (1986) suggest that "the process of negotiating the acquisition and integrating the target into the parent firm may also be prerequisites of success". The approach would allow to understand whether post-acquisition innovation performance of combined (acquired and acquiring) firms varies depending on the target integration mechanism.

9.3 Implications for Research

The present research work highlights that the existence of inter-organisational relationships does matter. In particular, alliances and CVC are an important and valuable signal of firm quality that give firms a competitive edge and should be evaluated when deciding which firms to acquire and when. This research brings in the signalling perspective to identify potential acquisition targets and shows that synergy-driven acquisitions of firms engaged in pre-acquisition relationships in the high technology industries enhance post-acquisition innovation outcomes of acquired firms consistent with value creation. Although the research finds a negative impact of an acquisition on the innovation outcomes for the combined firms, the sheer volume of acquisitions in high technology industry indicate that managers acquired firms with inter-organisational relationships as a mechanism to gain advantage from the operating potential of the connected targets.

The findings of this research are also important from an economic perspective. The rapid growth of technological innovations in the last few decades has meant that building and maintaining expertise in multiple business domains is challenging even for established corporations. Thus, bringing together firms with different innovation potential is becoming an important precondition to achieve success at innovation in many industries. The results of this study indicate the process of identifying innovative targets to increase potential at producing innovative output.

9.4 Implications for Practice

I present a fresh perspective on selecting acquisition targets and managers can gain a competitive edge by following this strategy. Few firms are involved in M&A and one might consider that managers make wise decisions when taking over firms. Even fewer firms acquire target firms engaged or not engaged in inter-organisational relationships. The research provides insights to managers seeking firms to acquire to rely on the information conveyed by their engagement in inter-organisational agreements. It brings forward the degree of importance of a firms' corporate connections to the managers and acknowledges the role of information carried by such relationships to alleviate concerns regarding quality of firms when selecting an acquisition target. Previous research has focused on prior relationships in a firm's portfolio or common connections and relationships between acquirers and targets which can introduce positive bias into the beliefs about the quality of a potential partner (Meschi et al., 2017; Rogan and Sorenson, 2014; Zaheer et al., 2010). This current research reveals that the direct connections of the targets enable acquirers to make appropriate decision about the quality of potential target firms and reduces the bias in perceptions of acquirers.

The research suggests that pre-acquisition inter-organisational relationships of the targets enable managers to better evaluate potential acquisition targets and achieve unique and valuable synergies, for example, innovation outcomes. Moreover, this study will facilitate managers to understand more reliable indicators of innovation outcomes and prove to be advantageous for them. Accordingly, managers can be encouraged to follow in this direction to search beyond their boundaries for targets engaged in inter-organisational relationships and assess their acquisition potential in terms of innovation performance. Managers engaging in acquisitions generally focus on short-term benefits to achieve efficiency through economies of scale and scope. To achieve long-term benefits managers will need to learn how to effectively manage and integrate acquired firms and the newly added targets relationships, and focus on creating superior value by developing novel products and breakthrough innovations through acquisitions of firms involved in partnerships.

This research shows that engaging in inter-organisational relationships can have two opposing outcomes on acquisition innovation performance. For acquired firms with inter-organisational relationships, the results suggest an increase in the overall innovation performance post-acquisition relative to acquired firms without inter-organisational relationships. On the other hand, acquiring targets with pre-acquisition inter-organisational relationships decreases innovation performance of merged firms after an acquisition. Achieving innovation growth is a time consuming and lengthy process and demands considerable effort. In order to accomplish competitive advantage, firms need to devise long term plans at managing the acquisition process. As synergies obtained from innovation growth are a crucial factor in acquisitions of high technology firms engaged in pre-acquisition inter-organisational relationships, managers need to devise a strategic plan for managing such acquisitions that would further expand their networks. An implication for the managers would be to recognise the challenges associated with such acquisitions. Another important factor for managers is to discern which relationships would be adding value and to keep maintaining those relationships. In contrast, relationships that are not productive or adding any value would need to be managed accordingly for an effective management of the acquisition process. Thus, this would require careful decision making by the managers. It could also mean that managers acquire targets that are technologically more advanced, as documented in their relationships, but maybe they have a worse fit with their own innovation capabilities. This seems to be an interesting trade-off in such acquisitions.

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APPENDIX A

TABLES AND FIGURES

Table A-1. The table below describes the dependent, independent, moderator and control variables of Study 1 on target firm selection model.

Variable	Definition and Measure
Dependent Variable:	
Acquisition	Deals where the acquiring firm increases its ownership and acquires at least 50% of the target firm's shares as a result of the takeover (Desyllas and Hughes, 2009). Measure: Binary variable; 1 if a firm is acquired, 0 otherwise.
Independent Variables:	
CVC Investments	Minority equity investments pursued by established corporations that extend their corporate venture capital arm to invest in entrepreneurial firms seeking capital for growing its operations (Dushnitsky, 2012; Gompers and Lerner, 1998). Measure: Total number of CVC investments a firm receives during the 3 year period leading to the last pre-acquisition year.
Alliances	Alliances are cooperative agreements between firms involving exchange, sharing, or co-development of products, technologies or services (Gulati, 1998). Alliances include R&D partnerships, joint ventures, licensing agreements, manufacturing and marketing alliances (Vanhaverbeke et al., 2002). Measure: Total number of alliances of a firm during the 3 year period leading to the last pre-acquisition year.
Moderator Variables:	
Start-up	Firms between the age of 5 and 12 (Bantel, 1998). Measure: Binary variable; 1 if a firm is 7 years or younger, 0 otherwise.
CVC Partner Reputation	Visibility in the media (Dimov et al., 2007). Measure: Binary variable; 1 if at least one of the investors affiliated with a firm is listed on the Midas list, 0 otherwise.
Alliance Partner Reputation	Media visibility as represented by the Fortune's Most Admired Companies survey (Filbeck et al., 2013). Measure: Binary variable; 1 if at least one of the alliance partners affiliated with a firm is listed on the Fortune's Most Admired Companies list.
Control Variables:	
Patent stock	Number of successful patent applications of a firm during the 3 year period leading to the last pre-acquisition year. The variable has been transformed to logarithm due to skewness.
Size	Natural logarithm of number of employees. The variable has been transformed to logarithm due to skewness.
Profitability	Return on total assets
Liquidity	Current assets/current liabilities

R&D Expenditure	R&D expense as reported in the database.
R&D Missing	A dummy variable equals 1 when R&D is missing and is 0 otherwise.
Private Firm Status	A dummy variable equals 1 if firm is held privately and 0 for public firms.
Industry dummy	Dummy variable; 2-digit Industry SIC codes; SIC 28, 35, 36, 37, 38, 48, 73, 87. The base industry is 28 at the 2-digit SIC code.
Year dummy	Year dummies for the period of observation; the base year is 2008

Table A-2. The table below provides a description of the dependent, independent and control variables of Study 2 on acquired firm innovation performance model.

Variable Name	Detailed Construction
Dependent Variable:	
Innovation Performance	Two measures were used: (i) Patent output: Total number of patents of a particular firm *i* in year *t* of observation. (ii) Citation output: Total number of citations received per patent of all patents of a firm *i* in year *t* of observation.
Independent Variables:	
CVC Investments	Total number of CVC investments of a firm *i* in year *t* of observation.
Alliances	Total number of alliances of a firm *i* in year *t* of observation.
Control Variables:	
Acquired Firm's Size	Natural logarithm of number of employees. The variable has been transformed to logarithm due to skewness.
Acquired Firm's Profitability	Return on total assets
Acquired Firm's Liquidity	Current assets/current liabilities
Acquired Firm's R&D Expenditure	R&D expense as reported in the database.
Acquired Firm's R&D Missing dummy	A dummy variable equals 1 when R&D is missing and is 0 otherwise.
Acquired Firm's Private Firm Status	A dummy variable equals 1 if firm is held privately and 0 for public firms.
Acquired Firm's Industry dummy	Dummy variable; 2 digit Industry SIC codes; SIC 28, 35, 36, 37, 38, 48, 73, 87. The base industry is 28 at the 2 digit SIC code.
Year dummy	Year dummies for the period of observation; the base year is 2008

Table A-3. The table below provides a description of the dependent, independent, and control variables of Study 3 on acquiring firms, measurement and source of data.

Variable Name	Measures
Dependent Variable:	
Innovation Performance	Two measures were used: (i) Patent output: Sum of the number of patents of each of the acquiring and acquired firm *i* in year *t* of observation. (ii) Citation output: Sum of the number of citations received per patents on all of the patents of each of the acquiring and acquired firm *i* in year *t* of observation.

Independent Variables:	
CVC Investments	Total number of CVC investments of an acquired firm *i* in year t of observation
Alliances	Total number of alliances of an acquired firm *i* in year t of observation.
Control Variables:	
Acquiring Firm's Size	Natural logarithm of number of employees (Mazzola et al., 2016)
Acquiring Firm's Profitability	Return on Total Assets (Dickerson et., 2002)
Acquiring Firm's Liquidity	Current assets/current liabilities (Desyllas and Hughes, 2009)
Acquiring Firm's R&D Expenditure	R&D expenditure as reported in the balance sheet from FAME.
Industry Relatedness	If acquiring and target firms are in the same 4-digit SIC codes, the dummy variable is coded 1 and 0 otherwise.
Acquiring Firm's Industry dummy	Dummy variable of 2 digit US SIC codes including 28, 35, 36, 37, 38, 48, 73 and 87.
Year dummy	Dummy variable of year of observation to account for year effects.

Table A-4. Results of the marginal effects at the mean – probability of being acquired.

	(1)	(2)	(3)
VARIABLES	margins	margins	margins
CVC Investments		0.0516***	0.107***
		(0.00848)	(0.0155)
Alliances		0.0103***	0.00807**
		(0.00257)	(0.00350)
Start-up			0.139***
			(0.0199)
CVC Partner Reputation			0.326
			(0.474)
Alliance Partner Reputation			0.827***
			(0.0975)
Liquidity (log)	-0.0108	-0.00905	-0.00219
	(0.00679)	(0.00671)	(0.00701)
Size (log)	-0.000377	-0.00422	0.00179
	(0.00391)	(0.00400)	(0.00413)
Profitability	0.000121	0.000293	0.000185
	(0.000226)	(0.000240)	(0.000242)
Patent stock (log)	0.00771	0.000235	0.00926
	(0.00838)	(0.00874)	(0.00852)
R&D Expenditure	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
R&D missing (dummy)	-0.0270	-0.0173	-0.0162
	(0.0174)	(0.0170)	(0.0172)
Private Firm Status (dummy)	0.0320	0.0405**	0.0278
	(0.0197)	(0.0189)	(0.0210)
Industry dummies	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes

Observations	3,798	3,798	3,798
Total No. of Firms	2302	2302	2302
Total No. of Acquired Firms	477	477	477
Total No. of Control Firms	1825	1825	1825

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-5. The average predicted probabilities computed using estimates of the logit model.

Average Predicted Probabilities: Acquisition Likelihood	
CVC Investments = 0 & Start-up = 0	0.0983075***
	(0.0053446)
CVC Investments = 0 & Start-up = 1	0.2118915***
	(0.0169326)
CVC Investments = 1 & Start-up = 0	0.1345112***
	(0.0099204)
CVC Investments = 1 & Start-up = 1	0.6312206***
	(0.1020291)
CVC Investments = 0 & Reputation = 0	0.1161876***
	(0.005239)
CVC Investments = 0 & Reputation = 1	0.3991632
	(0.4658983)
CVC Investments = 1 & Reputation = 0	0.2552898***
	(0.024642)
CVC Investments = 1 & Reputation = 1	0.3887989
	(0.4244043)
CVC Investments = 0 & Age = 0	0.1829193***
	(0.0125739)
CVC Investments = 0 & Age = 10	0.1507268***
	(0.0077552)
CVC Investments = 1 & Age = 0	0.5202187***
	(0.0814937)
CVC Investments = 1 & Age = 10	0.2339681***
	(0.0179349)
Alliances = 0 & Start-up = 0	0.1006631***
	(0.0054729)
Alliances = 0 & Start-up = 1	0.219648***
	(0.0169299)
Alliances = 1 & Start-up = 0	0.1058291***
	(0.0058177)

Alliances = 1 & Start-up = 1	0.2629255***
	(0.0209211)
Alliances = 0 & Reputation = 0	0.1213161***
	(0.005365)
Alliances = 0 & Reputation = 1	0.8362671
	(0.2213983)
Alliances = 1 & Reputation = 0	0.1301358***
	(0.0059178)
Alliances = 1 & Reputation = 1	0.815863
	(0.2247911)
Alliances = 0 & Age = 0	0.1900969***
	(0.012959)
Alliances = 0 & Age = 10	0.1552422***
	(0.007913)
Alliances = 1 & Age = 0	0.2281623***
	(0.0160281)
Alliances = 1 & Age = 10	0.1738575***
	(0.0087919)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-6. Target selection model: Results of the logit analysis – robustness check.

VARIABLES	(1) Acquisition	(2) Acquisition	(3) Acquisition	(4) Acquisition	(5) Acquisition
CVC Investments		0.473***	0.684***	1.201***	1.488***
		(0.0974)	(0.166)	(0.189)	(0.274)
Alliances		0.0988***	0.242***	0.0827***	0.225***
		(0.0242)	(0.0541)	(0.0285)	(0.0573)
Firm Age			-0.0221***		-0.0213***
			(0.00353)		(0.00355)
CVC Investments X Firm Age			-0.0230*		-0.0250*
			(0.0126)		(0.0143)
Alliances X Firm Age			-0.0101***		-0.00984***
			(0.00307)		(0.00310)
CVC Partner Reputation				2.682	4.119**
				(2.001)	(2.086)
CVC Investments X CVC Partner Reputation				-1.243***	-1.388***
				(0.258)	(0.272)
Alliance Partner Reputation				3.932**	3.796**
				(1.663)	(1.836)
Alliances X Alliance Partner Reputation				-0.238*	-0.242
				(0.133)	(0.150)
Liquidity (log)	-0.0876	-0.0736	-0.0166	-0.0592	-0.00573
	(0.0625)	(0.0635)	(0.0650)	(0.0645)	(0.0661)
Size (log)	-0.0133	-0.0401	0.0329	-0.0382	0.0353
	(0.0367)	(0.0380)	(0.0390)	(0.0385)	(0.0396)
Profitability	0.00103	0.00253	0.00237	0.000981	0.000825
	(0.00211)	(0.00228)	(0.00233)	(0.00223)	(0.00228)
Patent stock (log)	0.0613	0.000997	0.120	0.0339	0.140*
	(0.0784)	(0.0825)	(0.0815)	(0.0817)	(0.0808)
R&D Expenditure	0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D missing (dummy)	-0.167	-0.143	-0.176	-0.144	-0.189
	(0.144)	(0.148)	(0.150)	(0.151)	(0.152)
Private Firm Status (dummy)	0.250	0.423*	0.291	0.426*	0.302
	(0.226)	(0.239)	(0.239)	(0.243)	(0.243)
Prior ties (dummy)	1.556***	0.320	0.374	-0.966*	-0.854*

	(0.216)	(0.347)	(0.351)	(0.513)	(0.517)
Domestic acquisition (dummy)	-0.0219	-0.0338	-0.0631	-0.0170	-0.0483
	(0.109)	(0.110)	(0.112)	(0.112)	(0.113)
Related (dummy)	0.0535	0.0593	0.100	0.0221	0.0559
	(0.135)	(0.138)	(0.138)	(0.140)	(0.141)
Industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	-1.992***	-2.095***	-1.713***	-2.151***	-1.773***
	(0.365)	(0.375)	(0.380)	(0.381)	(0.385)
Chi–square	52.34	106.2	186.3	160.1	236.2
Pseudo R–square	0.0182***	0.0370***	0.0649***	0.0558***	0.0823***
Log likelihood	-1409	-1382	-1342	-1355	-1317

N_{it} = 3798; N_i = 477. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A-7. Target selection model: Results of the logit analysis – robustness checks.

	(1)
VARIABLES	Acquisition
CVC Investments (high reputation of partner)	-3.374***
	(0.759)
CVC Investments (other)	0.892***
	(0.128)
Alliances (high reputation of partner)	-1.372
	(1.098)
Alliances (other)	0.0968***
	(0.0257)
Start-up	0.689***
	(0.137)
Firm Age	-0.0149***
	(0.00371)
Liquidity (logarithm)	0.00308
	(0.0659)
Size (logarithm)	0.0357
	(0.0390)
Profitability	0.00177
	(0.00229)
Patent stock (log)	0.0583
	(0.0814)
R&D Expenditure	-0.0658
	(0.0598)
R&D missing (dummy)	-0.612
	(0.385)
Private Firm Status (dummy)	0.319
	(0.241)

Industry dummies	Yes
Year dummies	Yes
Constant	-1.629***
	(0.521)
Observations	3,798
Total No. of Firms	2302
Total No. of Acquired Firms	477
Total No. of Control Firms	1825
Pseudo R^2	0.0722***
Chi^2	207.4
Log Likelihood	-1332

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-8. Target selection model: Results of the logit analysis – controlling for prior ties.

VARIABLES	(1) Acquisition	(2) Acquisition	(3) Acquisition	(4) Acquisition	(5) Acquisition
CVC Investments		0.535***	0.430***	0.938***	0.391***
		(0.0744)	(0.0737)	(0.115)	(0.141)
Alliances		0.0972***	0.0552*	0.0826***	-0.0222
		(0.0243)	(0.0303)	(0.0287)	(0.0517)
Start-up			0.878***		1.143***
			(0.125)		(0.117)
Start-up X CVC Investments			0.806**		1.101***
			(0.323)		(0.283)
Start-up X Alliances			0.187***		0.347***
			(0.0714)		(0.0880)
CVC Partner Reputation				1.880	9.093
				(1.996)	(9.867)
CVC Partner Reputation X CVC Investments				-0.995***	-1.642*
				(0.216)	(0.969)
Alliance Partner Reputation				3.919**	6.031**
				(1.649)	(2.880)
Alliance Partner Reputation X Alliances				-0.238*	-0.487*
				(0.133)	(0.261)
Liquidity (log)	-0.0989	-0.0747	-0.0356	-0.0593	0.0189
	(0.0622)	(0.0635)	(0.0661)	(0.0645)	(0.0681)
Size (log)	-0.00361	-0.0372	0.0190	-0.0373	0.0556
	(0.0360)	(0.0379)	(0.0389)	(0.0385)	(0.0405)
Profitability	0.00113	0.00263	0.00339	0.000983	0.00122
	(0.00207)	(0.00228)	(0.00237)	(0.00223)	(0.00243)
Patent stock (log)	0.0715	0.00505	0.0683	0.0347	0.0860
	(0.0769)	(0.0823)	(0.0812)	(0.0820)	(0.0853)
R&D Expenditure	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D Expenditure (missing)	-0.232	-0.145	-0.142	-0.144	-0.120
	(0.142)	(0.148)	(0.150)	(0.151)	(0.155)

Prior ties (dummy)	-0.0188	-0.0330	-0.203	-0.185	-0.914
	(0.488)	(0.494)	(0.536)	(0.525)	(0.703)
Private firm status (dummy)	0.327	0.423*	0.302	0.416*	0.246
	(0.225)	(0.239)	(0.238)	(0.243)	(0.248)
Diversify (dummy)	-0.0332	-0.0691	-0.102	-0.0834	-0.0297
	(0.142)	(0.146)	(0.149)	(0.147)	(0.156)
Domestic (dummy)	0.00401	-0.0249	0.0369	-0.0186	0.0513
	(0.104)	(0.107)	(0.109)	(0.109)	(0.113)
Industry dummies	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes
Constant	-1.978***	-2.030***	-2.379***	-2.078***	-2.752***
	(0.382)	(0.394)	(0.402)	(0.400)	(0.419)
Observations	3,798	3,798	3,798	3,798	3,798
Pseudo R^2	0.00245	0.0365	0.0673	0.0543	0.122
Chi^2	7.026***	104.9***	193.2***	155.8***	350.8***
Log likelihood	-1432	-1383	-1339	-1357	-1260
No. of acquired firms			477		
No. of non-acquired firms			1825		
Total no. of firms			2302		

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A-9. Target Firm's Two Digit Standard Industry Classification (SIC) Codes.

SIC Codes	Standard Industry Classification Code Description
28	Chemicals and Allied Products
35	Industrial and Commercial Machinery and Computer Equipment
36	Electronics and Electrical Equipment
37	Transportation Equipment
38	Measuring, Analysing and Controlling Instruments, Photographic, Medical and Optical Goods
48	Communications
73	Business Services
87	Engineering, Accounting, Research, Management and Related Services

Table A-10. Acquiring Firm's Two Digit Standard Industry Classification (SIC) Codes.

SIC Codes	Standard Industry Classification Code Description
15	Building Construction
17	Construction
28	Chemicals and Allied Products

34	Fabricated Metal Products (except machinery and transportation equipment)
35	Industrial and Commercial Machinery and Computer Equipment
36	Electronics and Electrical Equipment
37	Transportation Equipment
38	Measuring, Analysing and Controlling Instruments; Photographic, Medical and Optical Goods
39	Miscellaneous Manufacturing Industries
48	Communications
50	Wholesale Trade (Durable Goods)
60	Depository Institutions
61	Non-Depository Credit Institutions
62	Security and Commodity Brokers, Dealers, Exchanges and Services
63	Insurance Carriers
64	Insurance Agents, Brokers, and Service
67	Holding and Other Investment Offices
72	Personal Services
73	Business Services
80	Health Services
87	Engineering, Accounting, Research, Management and Related Services

Figure A-1. CVC-Startup Interaction Effects after Logit

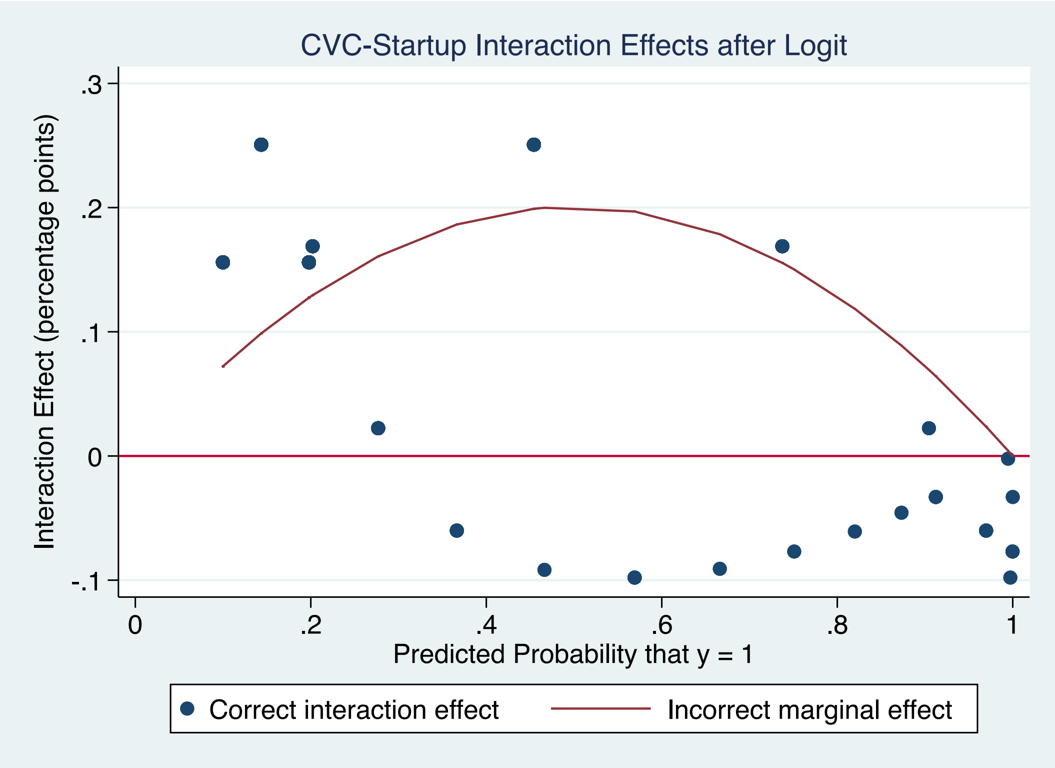


Figure A-2. CVC-Startup Z-Statistics of Interaction Effects after Logit

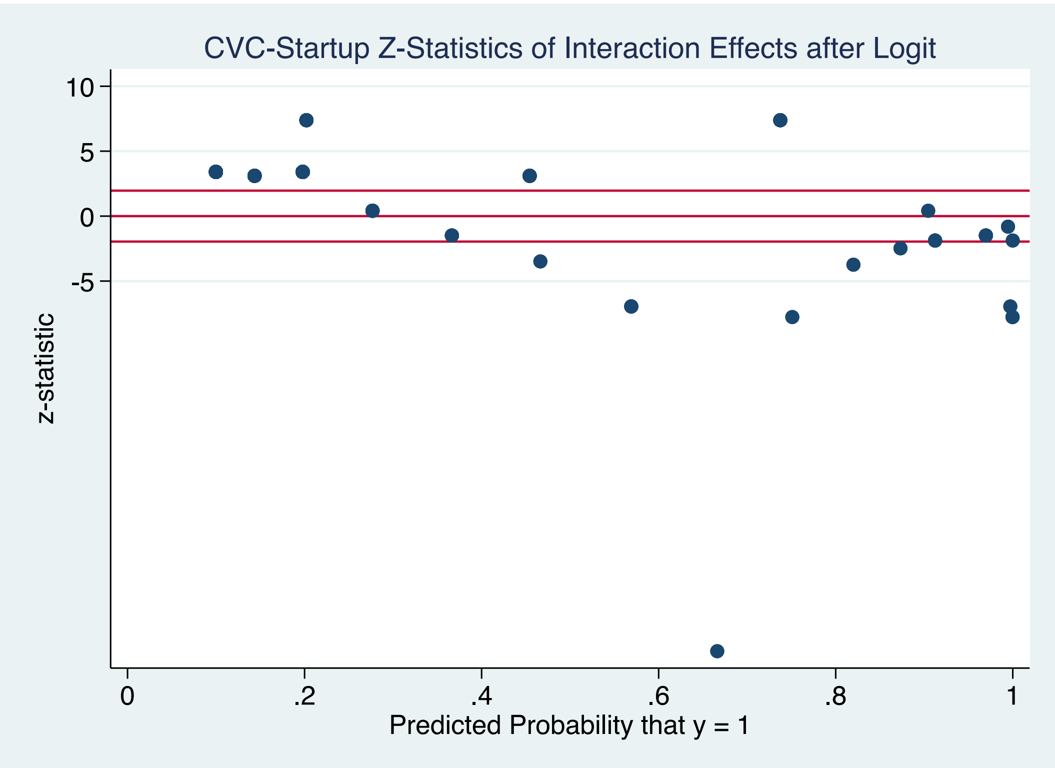


Figure A-3. Alliance-Startup Interaction Effects after Logit

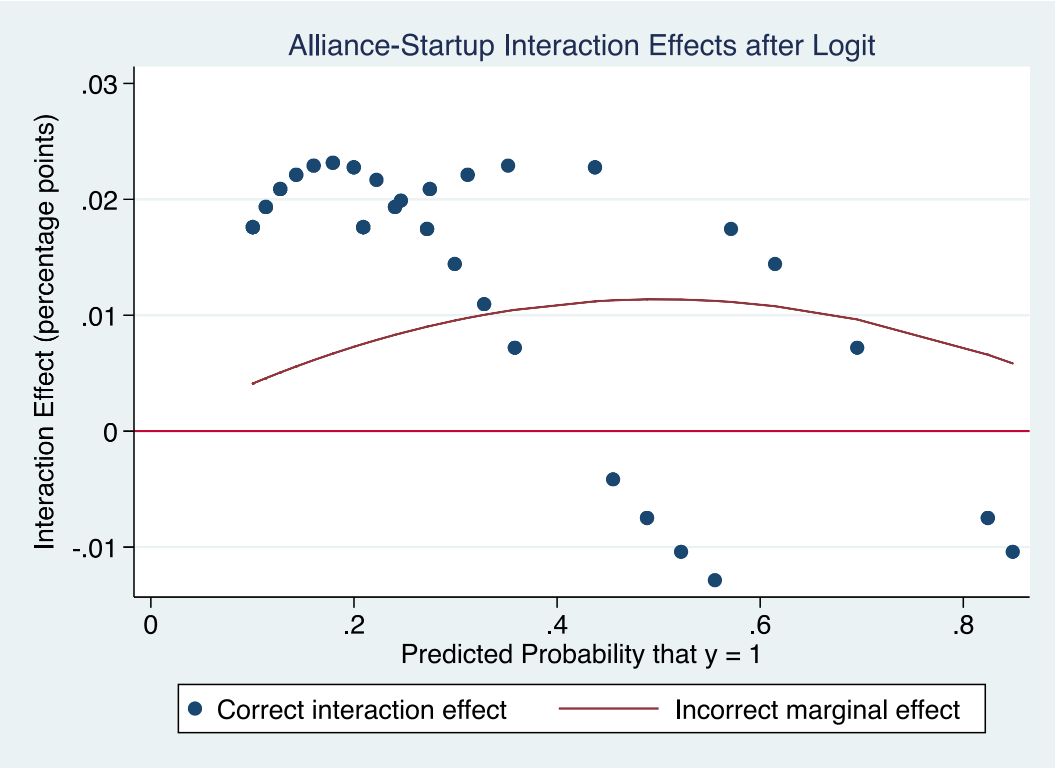


Figure A-4. Alliance-Startup Z-Statistics of Interaction Effects after Logit

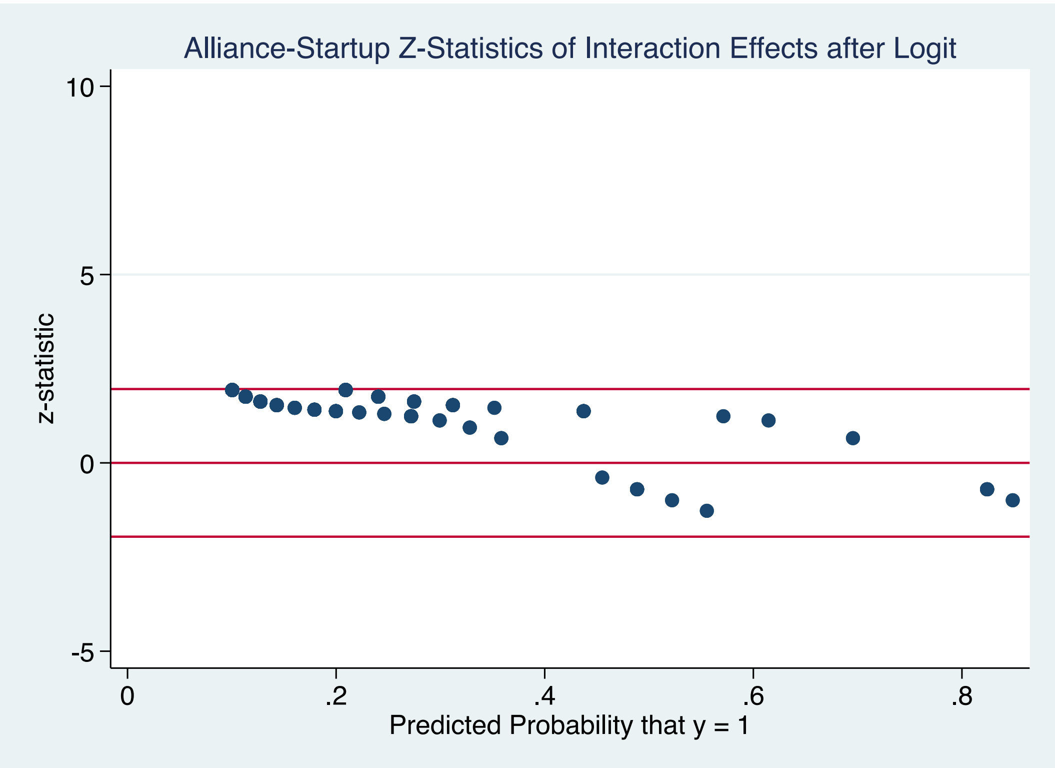


Figure A-5. CVC-Reputation of CVC Investor Interaction Effects after Logit

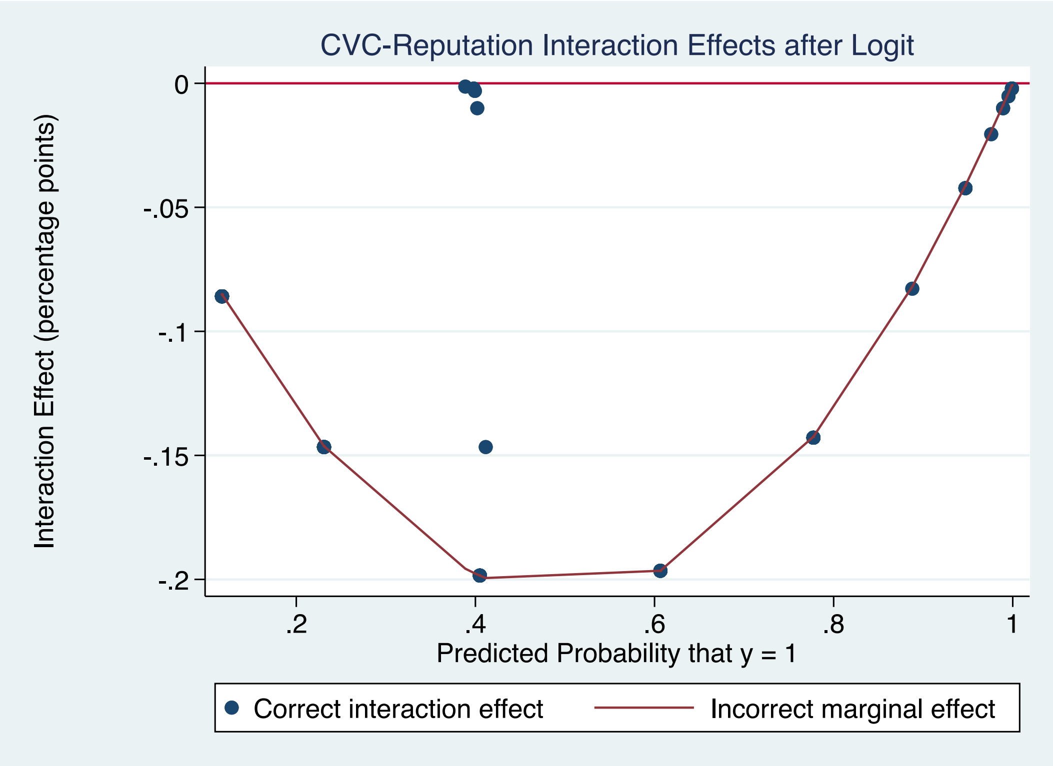


Figure A-6. CVC-Reputation of CVC Investor Z-Statistics Interaction Effects after Logit

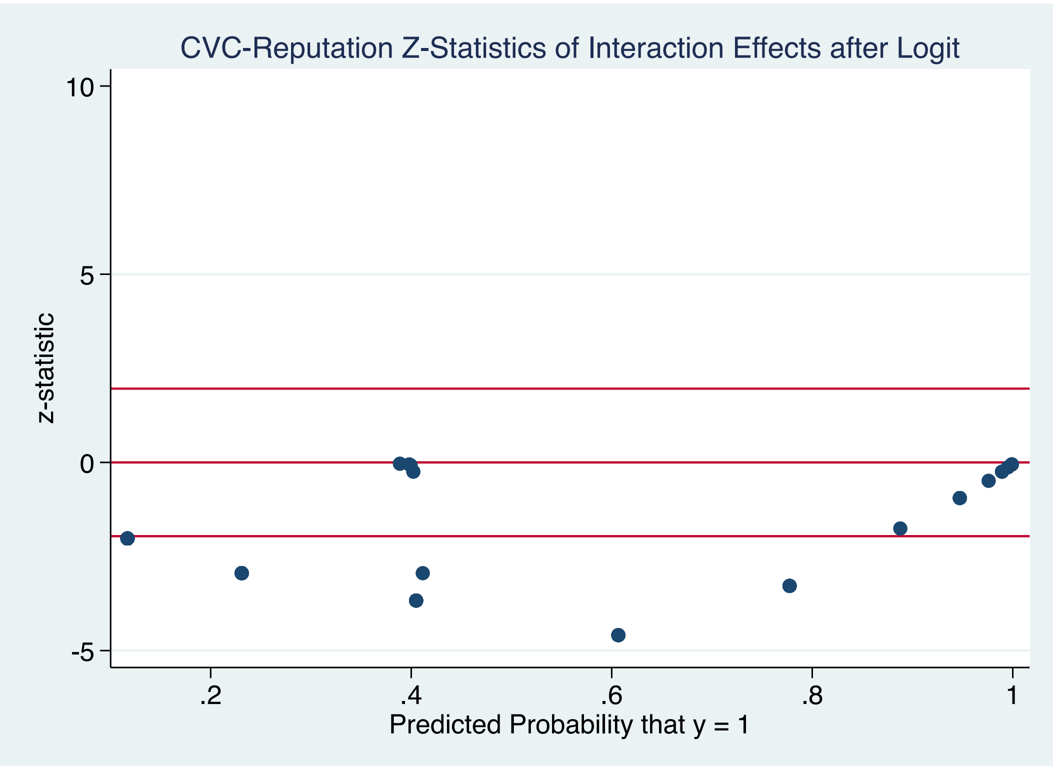


Figure A-7. Alliance-Reputation of Alliance Partner Interaction Effects after Logit

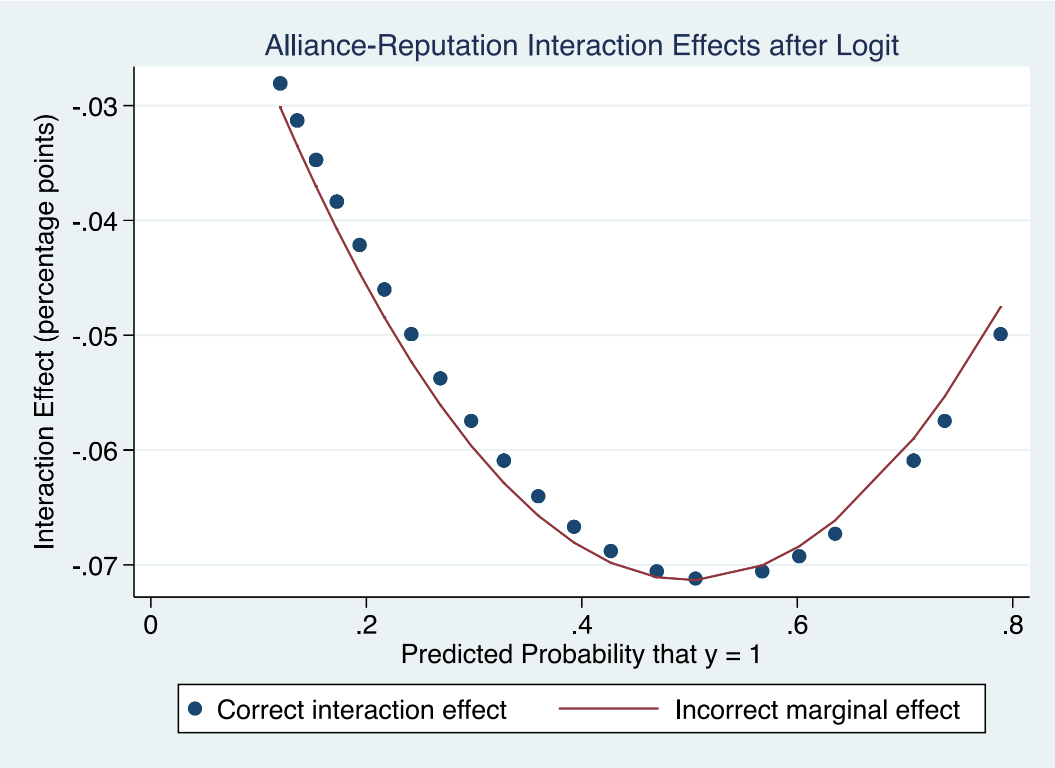


Figure A-8. Alliance-Reputation of Alliance Partner Z-Statistics Interaction Effects after Logit

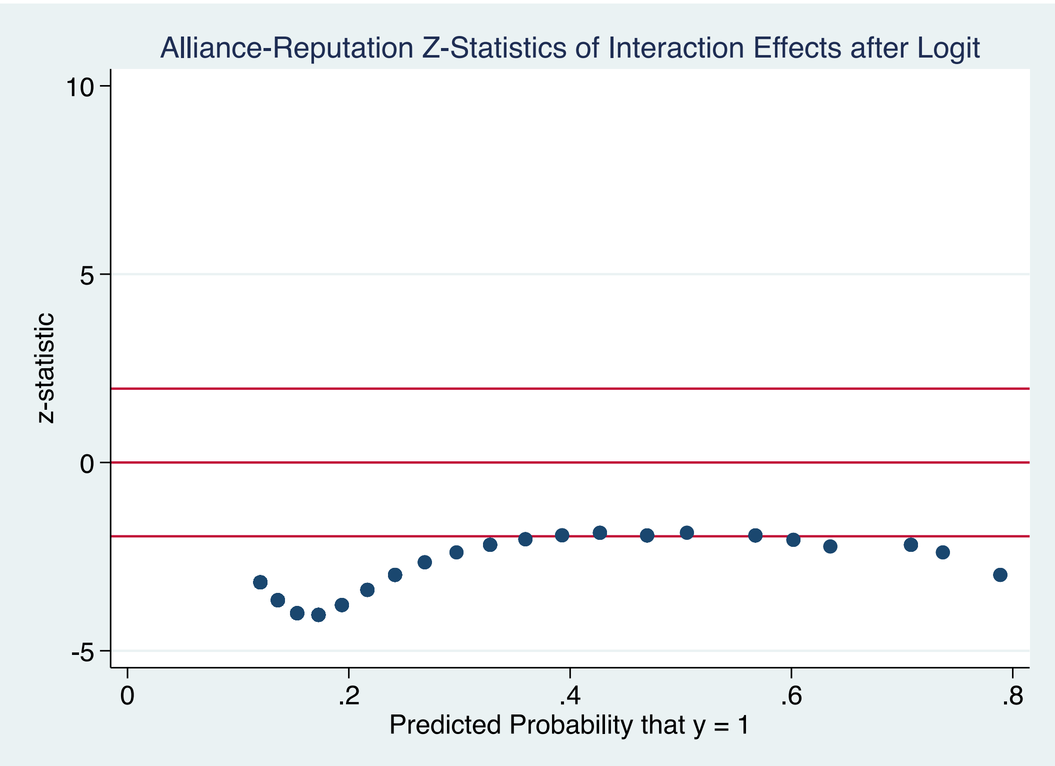


Figure A-9. CVC-Age Interaction Effects after Logit

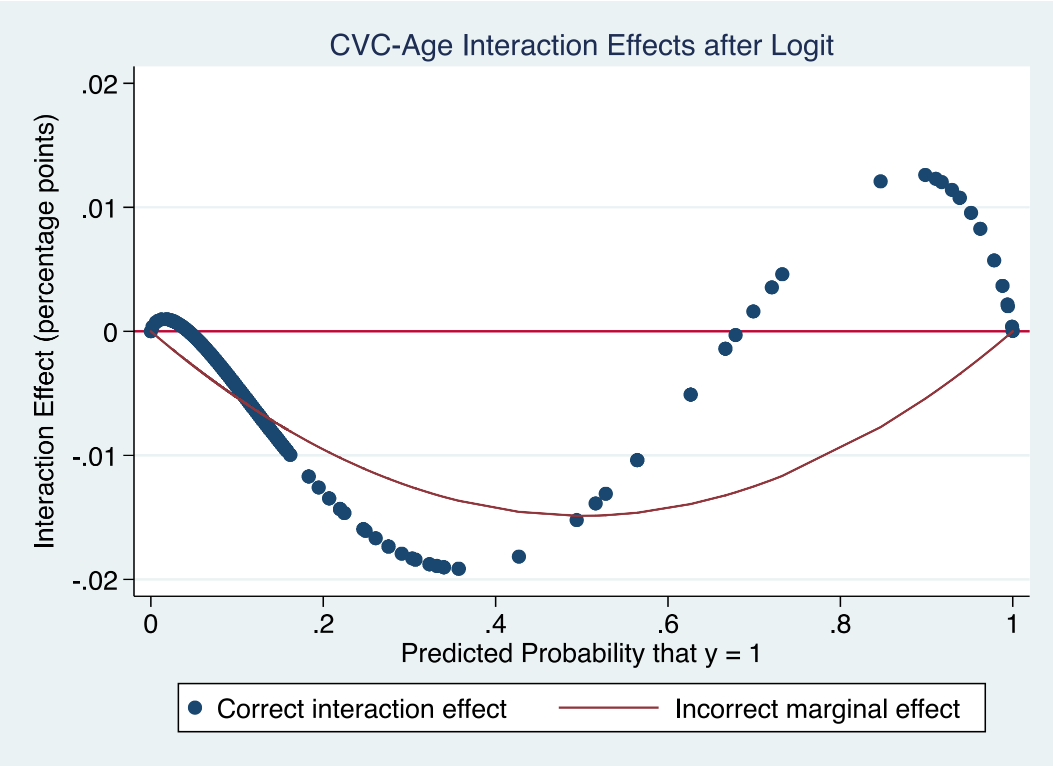


Figure A-10. CVC-Age Z-Statistics Interaction Effects after Logit

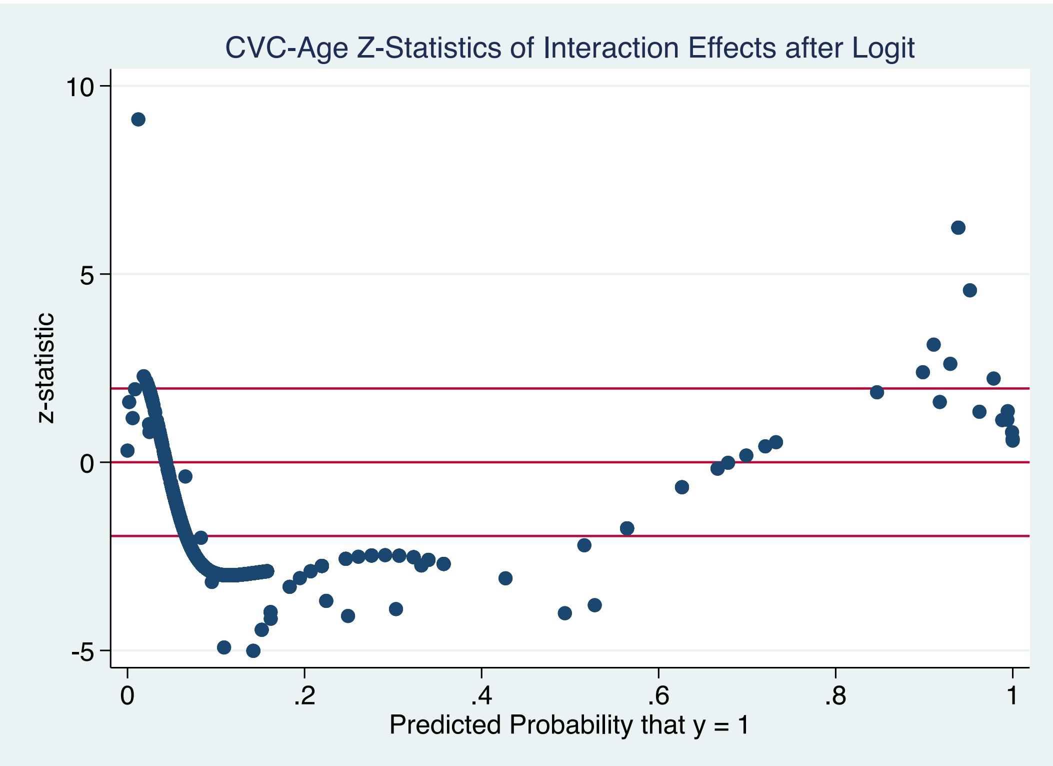


Figure A-11. Alliance-Age Interaction Effects after Logit

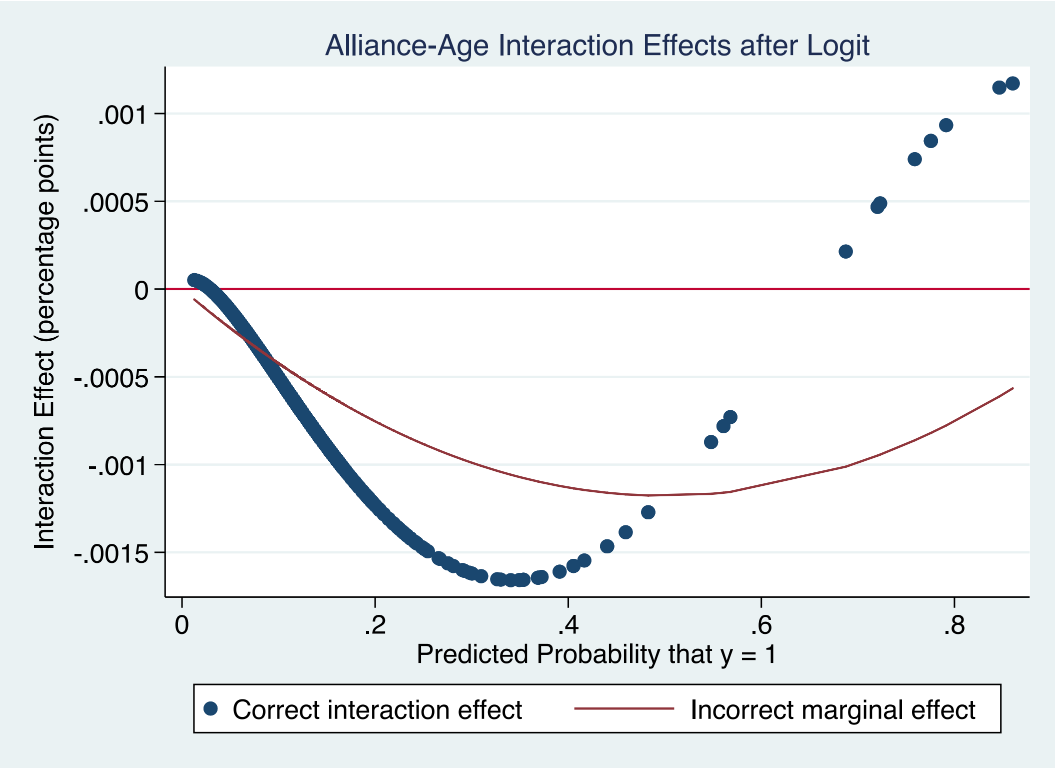
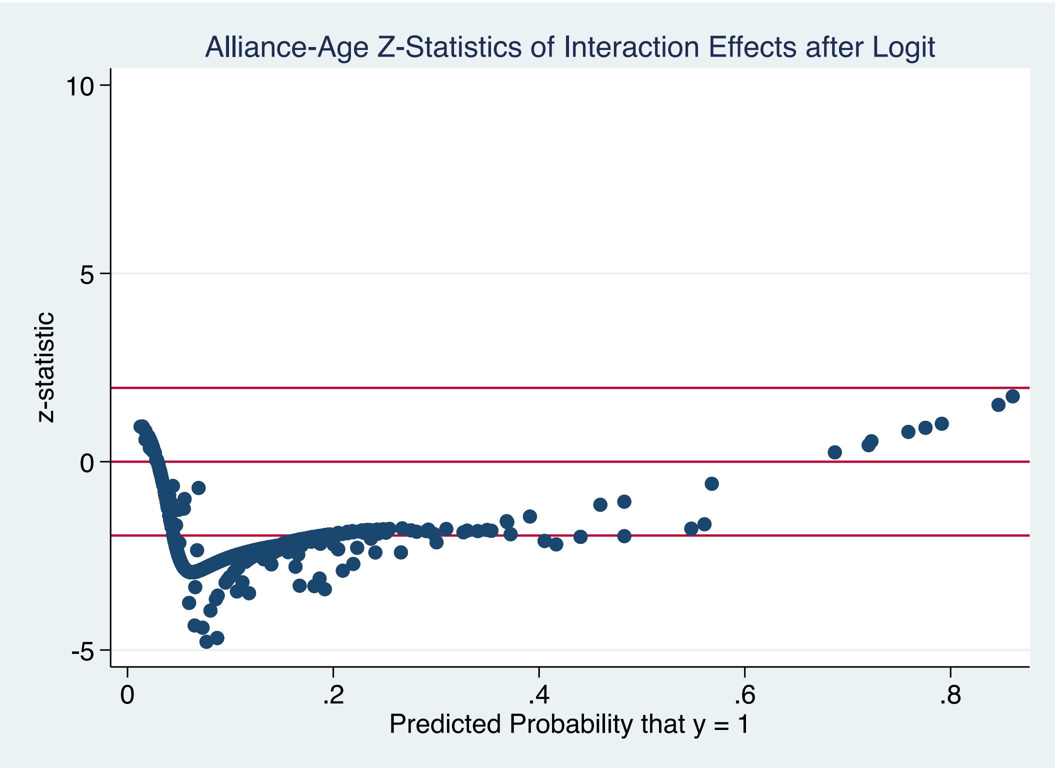
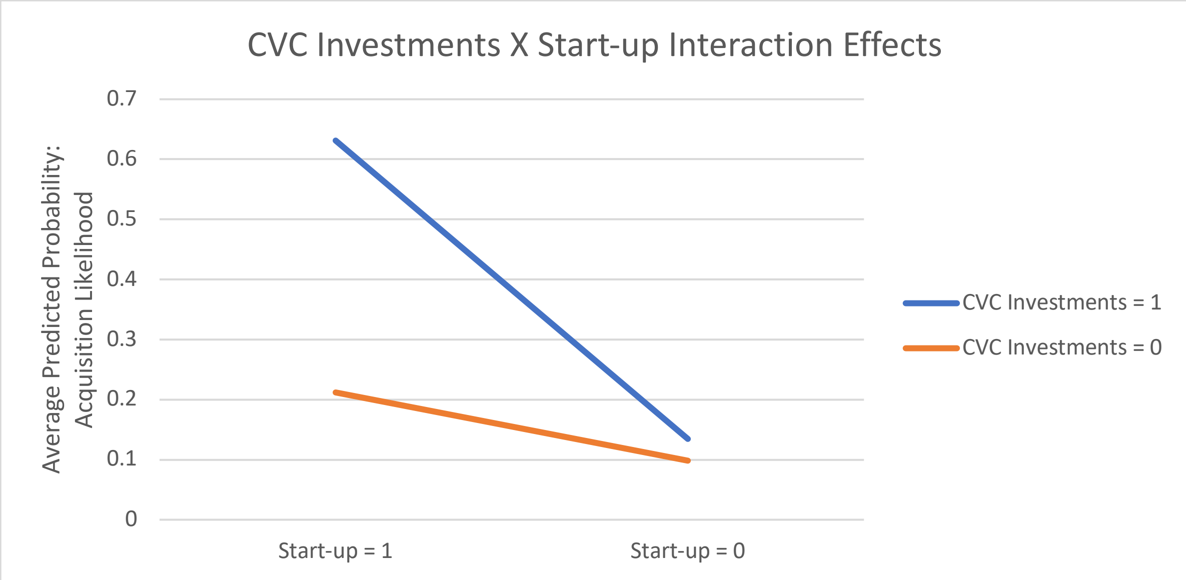
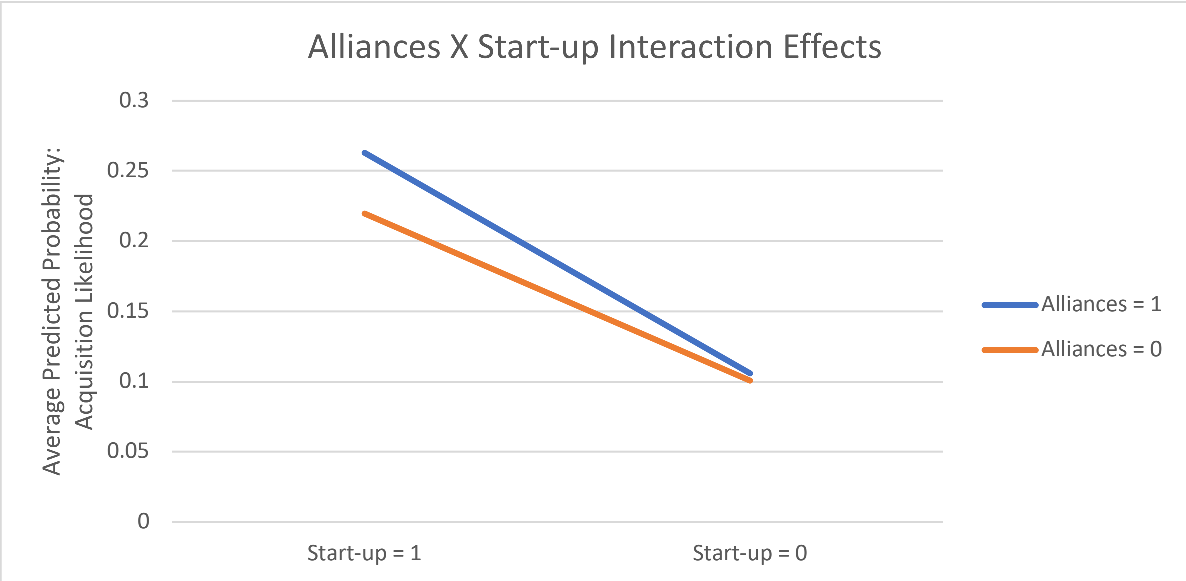
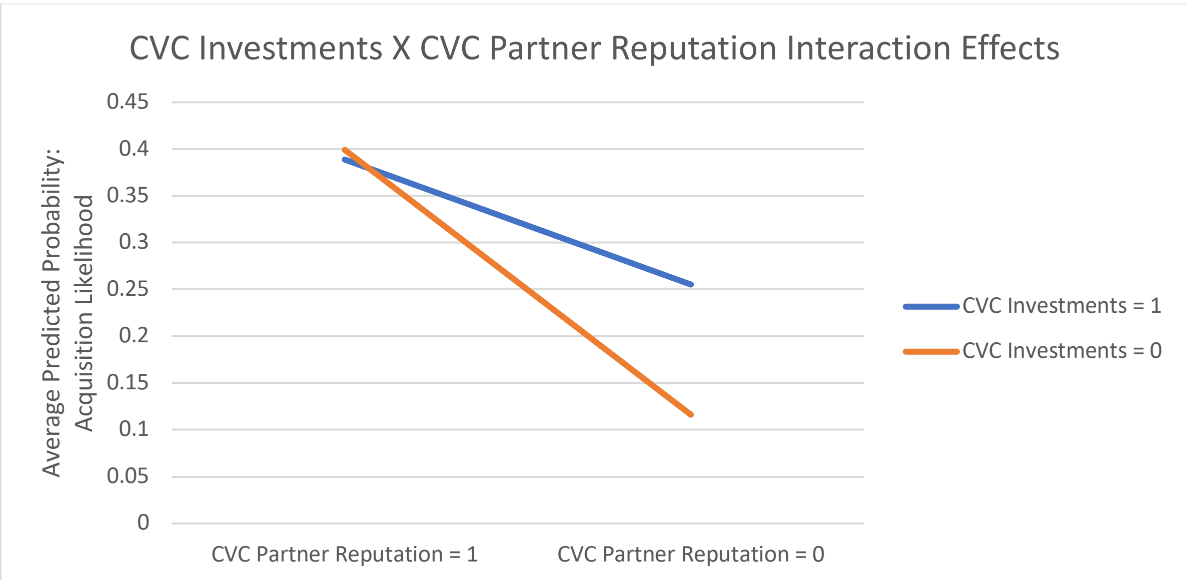


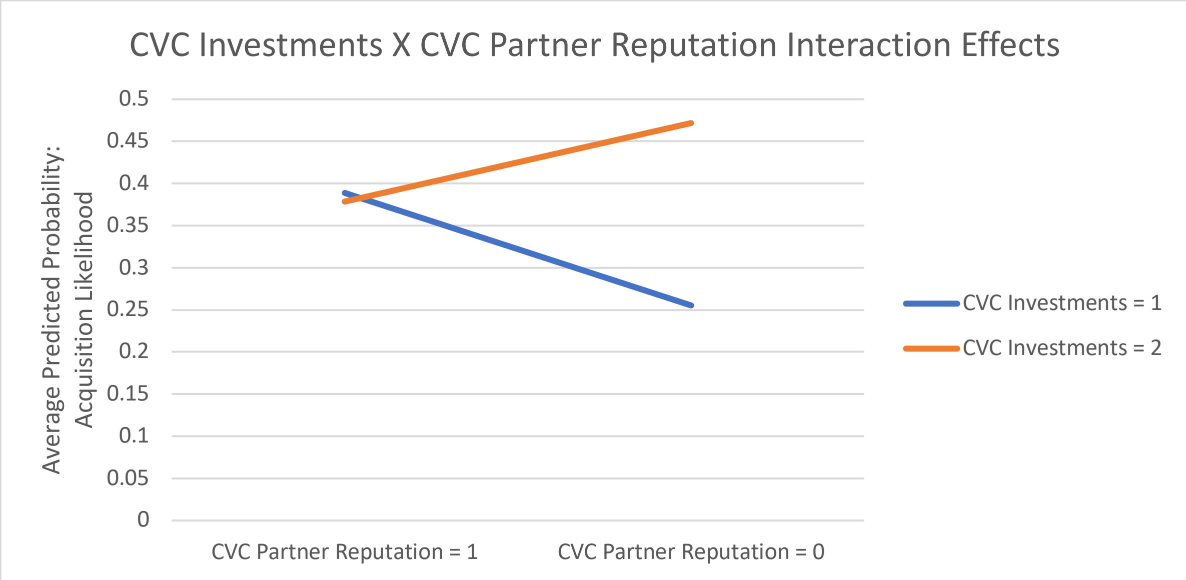
Figure A-12. Alliance-Age Z-Statistics Interaction Effects after Logit

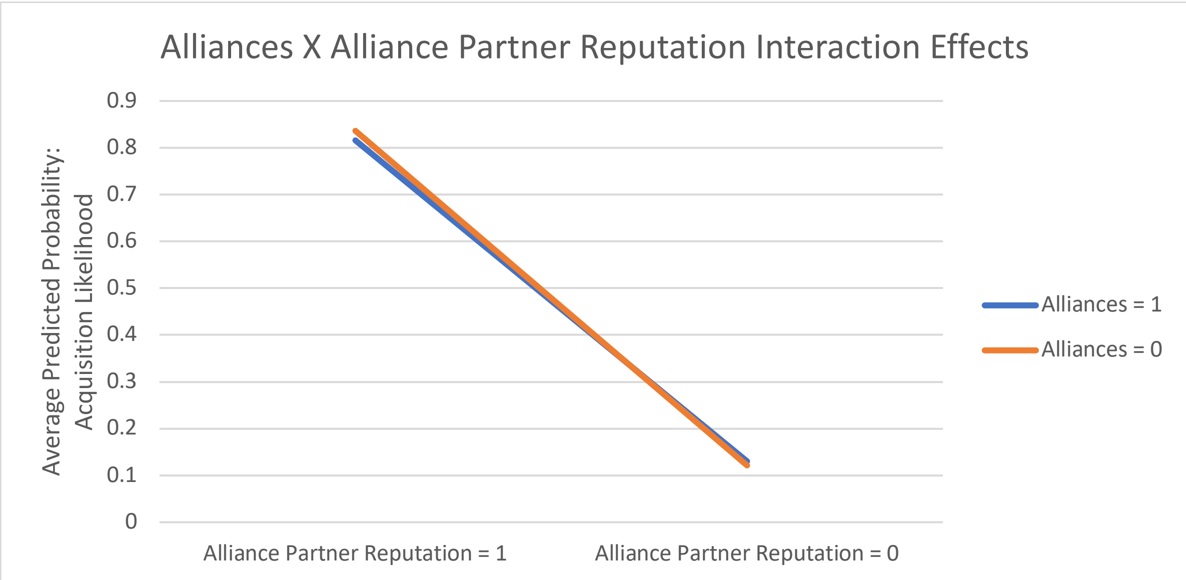


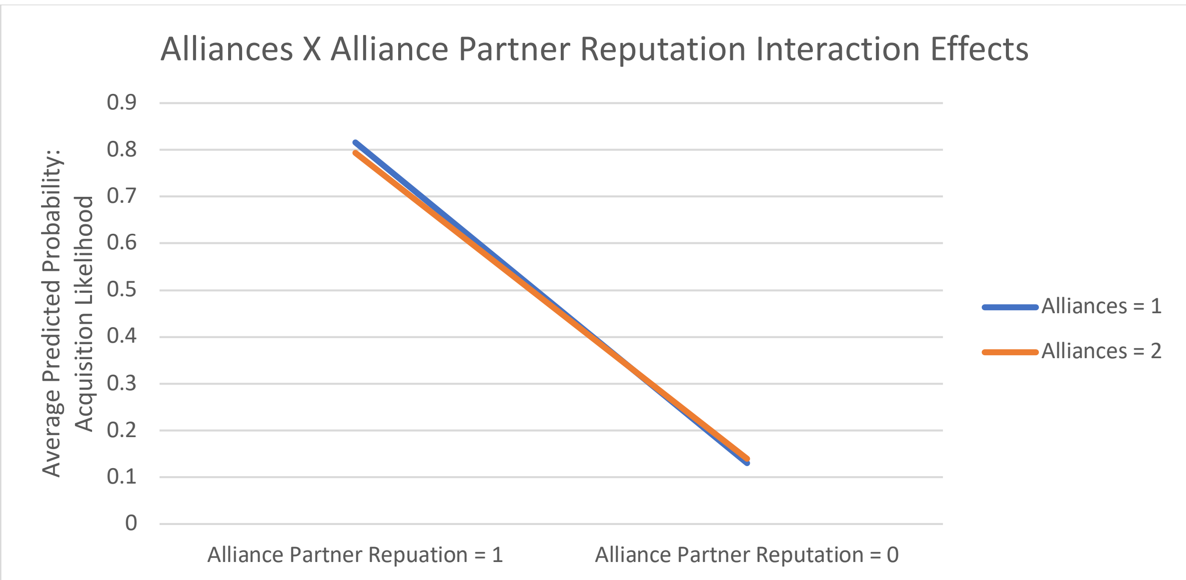

CVC Investments X Start-up Interaction Effects
Average Predicted Probability: Acquisition Likelihood
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Start-up = 1
Start-up = 0
CVC Investments = 1
CVC Investments = 0


Alliances X Start-up Interaction Effects
Average Predicted Probability: Acquisition Likelihood
0.3
0.25
0.2
0.15
0.1
0.05
0
Start-up = 1
Start-up = 0
Alliances = 1
Alliances = 0


CVC Investments X CVC Partner Reputation Interaction Effects
Average Predicted Probability: Acquisition Likelihood
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
CVC Partner Reputation = 1
CVC Partner Reputation = 0
CVC Investments = 1
CVC Investments = 0


CVC Investments X CVC Partner Reputation Interaction Effects
Average Predicted Probability: Acquisition Likelihood
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
CVC Partner Reputation = 1
CVC Partner Reputation = 0
CVC Investments = 1
CVC Investments = 2


Alliances X Alliance Partner Reputation Interaction Effects
Average Predicted Probability: Acquisition Likelihood
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Alliance Partner Reputation = 1
Alliance Partner Reputation = 0
Alliances = 1
Alliances = 0


Alliances X Alliance Partner Reputation Interaction Effects
Average Predicted Probability: Acquisition Likelihood
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Alliance Partner Repuation = 1
Alliance Partner Reputation = 0
Alliances = 1
Alliances = 2

APPENDIX B

PYTHON MAPPING CODE PROCEDURE

*************MAPPING BETWEEN PATENT DATABASES AND FAME************

Overview of mapping example:

The module **pygingpy** contains a class called *map* which provides functionality for linking between two datasets when a field contains a unique member but inconsistent and different entries between and within the two datasets.

The original example problem was to map company names which might be variously described as:

'My Apple Company Ltd', 'My Apple Company, Ltd', 'My Apple Company, Ltd.', 'My Apple Company LTD.'

This notebook describes how you can use **pyginpy:** *map* to quickly resolve this problem. It should guide you through each step of the process and provide a template for identifying, verifying and applying your own maps.

pyginpy is implemented in python but with the aim of being readily usable, and is intended to be light touch allowing developers/researchers to determine a map, apply it to their data and export modified data to be used in their preferred environment/framework.

If you are not familiar with Jupyter Notebooks it is advised to work through the cells in order or use **run all** *from the cell tab at the top of the notebook.*

Approach:

map makes certain assumptions about your datasets.

- One of these is a reference dataset which contains the set of members of interest.

e.g. if the field of interest contains: 'My Apple Company Ltd', 'My Apple Company, Ltd', etc., then they will be considered separate entries.

- The second match dataset may contain any or all variations which are mapped to the reference dataset.
- The datasets are read in and processed to identify any duplicates, i.e. identical entries within each dataset.

The map is developed for each instance of a given member, so duplicates are unnecessary to determine the map. When assigning the map all instances are mapped if one has been determined.

- Exact matches in the reference dataset are identified e.g. where 'My Apple Company Ltd' exists in both.
- *Inexact* matches in the reference dataset are identified:
- Strings are split on white space.
- Punctuation is stripped from resulting strings.
- Strings are forced to lowercase.
- **A dictionary mapping is applied to replace one string with another.**
- The resulting strings are joined to produce a single string, all lowercase with no spaces or punctuation.

Thus, the four examples: 'My Apple Company Ltd', 'My Apple Company, Ltd', 'My Apple Company, Ltd.', 'My Apple Company LTD.', would all be mapped to the same ID.

- Apply the map by creating a new field mapid0 in each data set, containing the ID or left empty if not found.
- Export new datafiles in preferred data format.

Set-up:

The **pyginpy** library automatically loads all dependencies that it requires, so to set-up we just need to import the map functionality and create a map object.

From pyginpy import map

Set file, path and type variables:

We set variables for the filename, datatype for the reference and match datasets. We also provide the relative datapath. Note that in our example two datasets are in the same location, but this is not required and paths can be set separately.

Currently provisioned datatypes are:

- Excel: ['excel', 'xls', 'xlsx']
- Stata: ['dta', 'stata']
- Csv: ['csv <#>']
    - where csv is assumed comma or followed by optional delimiter e.g. csv ;

Read in your datasets

Here we specify the data file, for example, ‘targetsample.xls’.

Set fields to map

Here we specify the variables to match, for example, ‘Companyname’.

Set dictionary for map

Here we specify keywords or dictionary to replace a series of words with an empty string:

For example, my key words = { ‘ltd’ : ‘’,

‘limited’: ‘’,

'corporation': ''}

Process data:

This may be automated with a single function at a later date but is reproduced explicitly to explain how the map is generated:

- First identify the unique members in each of the datasets
- Then prepare the map from reference data and initialise the match dataset for mapping
- Exact_map finds the common members of the original datasets
- Inexact map finds the common members when whitespace, punctuation have been stripped and forced to lower case as detailed above.
- Finally a reverse map is generated from the original members to the unique ID.

At each stage the maps are exported to the original datapath with filenames `exact.yaml` and `inexact.yaml`.

Append map and export new data files:

Assuming that the you are only trying to match between one pair of fields at a time, a new field/column `mapid0` will have been appended to each dataset. This will contain the unique ID to allow mapping/merging between datasets or in the case of match dataset will be empty if no map has been generated.

APPENDIX C

STATA CODE

** Thesis: The Role of Inter-organisational Relationships of Firms on the Selection **

** of Takeover Targets and their Impact on Post-Acquisition Innovation Performance **

** of Acquired and Combined (Acquired and Acquiring) Firms **

************************************** Huma Javaid ********************************

****** Study 1: Target Firm Selection Model ******

```
* import excel file
import excel "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample before CEM_data.xls", sheet("Sheet1") firstrow
ssc install cem
ssc install outreg2
ssc install estout
ssc install tabout

***************** Label variables ********************

label variable newid "Acquired Firm ID"
label variable year "acquisition year"
label variable targetname "Acquired Company Name"
label variable treated1 "Acquired firm"
label variable treated1percentageacquired "Percentage acquired of firm"
label variable regnumber "Acquired Firm Registered Number"
label variable bvdid "Acquired Firm BVD ID"
label variable country "Acquired Firm Country"
label variable industrySIC "Acquired Firm 4-digit Industry SIC Code"
```

```
label variable threedigitSIC "Acquired Firm 3-digit Industry SIC Code"
label variable twodigitSIC "Acquired Firm 2-digit Industry SIC Code"
label variable status "Acquired Firm Private Status"
label variable liquidity "Acquired Firm Liquidity"
label variable size "Acquired Firm Size"
label variable roa "Acquired Firm Profitability"
label variable CVC "Corporate Venture Capital Investments"
label variable alliance "Strategic Alliances"
label variable rand "Acquired Firm R&D Expenditure"
label variable doiyear "Acquired Firm Date of Incorporation"
label variable CVCreputation "CVC Partner Reputation"
label variable Reputationalliance "Alliance Partner Reputation"

//desc

* dummy variables

sum

// generate a dummy variable for acquisition

gen acquisition=1 if treated1==1 & treated1percentageacquired>=50
replace acquisition=0 if missing(acquisition)
tab acquisition

// generate a dummy variable for acquired firms' private status

tab status
gen dstatus=1 if status=="Private Limited"
replace dstatus=0 if missing(dstatus)
tab dstatus
```

```
/*generate a dummy variable for missing R&D expenditure values of acquired firm
following Desyllas and Hughes (2009)*/

tab rand
gen dnorand=1 if missing(rand)
replace dnorand=0 if missing(dnorand)
replace rand=0 if missing(rand)

// generate age of acquired firm

gen age = ( year) - (doiyear)
tab age

// generate dummy variable for start-up firm moderator variable
gen startup7years=1 if age<=7
replace startup7years=0 if missing(startup7years)
tab startup7years

// Label the new variables

label variable acquisition "Acquisition"
label variable dstatus "Acquired Firm Private Status Dummy Variable"
label variable dnorand "Acquired Firm R&D Expenditure missing dummy"
label variable age "Acquired Firm Age"
label variable startup7years "Startup firms aged 7 years"

* log transformation and winsorizing

sum
```

```
//desc

// generate log transformed variable for acquired firm liquidity
gen lnliquidity = ln(liquidity)

// winsorize log transformed acquired firm liquidity variable
winsor2 lnliquidity, cut(1 99)

// draw histogram of winsorized acquired firm liquidity variable
histogram lnliquidity_w

// generate log transformed variable for acquired firm size
gen lnsize = ln(size)

// winsorize log transformed acquired firm size variable
winsor2 lnsize, cut(1 99)

// draw histogram of log transformed acquired firm size variable
histogram lnsize_w

// winsorize acquired firm profitability variable
winsor2 roa, cut(1 99)

// draw histogram of acquired firm profitability variable
histogram roa_w

// generate log transofrmed variable of acquired firms' patents

gen patentcount = (1) + (totalpatents)
gen lnpatentcount = ln(patentcount)
```

```
//Label the new variables

label variable lnliquidity "Acquired Firm Liquidity log transformed"
label variable lnliquidity_w "Acquired Firm Liquidity winsorized"
label variable lnsize "Acquired Firm Size log transformed"
label variable lnsize_w "Acquired Firm Size winsorized"
label variable roa_w "Acquired Firm Profitability winsorized"
label variable totalpatents "Acquired Firm Patents"
label variable patentcount "Acquired firm patent count"
label variable lnpatentcount "Acquired Firm patents log transformed"

//desc

/*destring variables*/

destring, replace
sum, detail

* coarsened exact matching (CEM)

//desc

describe, short

/*descriptive statistics before CEM*/

sum
sum if treated1==1
sum if treated1==0

imb lnsize_w roa_w industrySIC year, tr(treated1)
```

```
cem lnsize_w roa_w industrySIC(#0) year(#0), tr(treated1) showbreaks
tab cem_matched

//Label the new variables

label variable cem_strata "Acquired Firm cem_strata"
label variable cem_matched "Acquired Firm cem_matched"
label variable cem_weights "Acquired Firm cem_weights"

/*descriptive statistics after CEM*/

sum
sum if treated1==1
sum if treated1==0
pwcorr treated1 CVC alliance lnliquidity_w lnsize_w roa_w rand dnorand age startup7years CVCreputation Reputationalliance lnpatentcount dstatus, star(0.05)

*********** Logit regression on CEM matched data ************************

logit treated1 lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]
outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample results full model.xls", e(all)
logit treated1 CVC alliance lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]
outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample results full model.xls", e(all)
logit treated1 c.CVC##i.startup7years c.alliance##i.startup7years lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]
outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample results full model.xls", e(all)
logit treated1 c.CVC##i.CVCreputation c.alliance##i.Reputationalliance lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]
```

```
outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample results full model.xls", e(all)

logit treated1 c.CVC##i.startup7years c.alliance##i.startup7years c.CVC##i.CVCreputation c.alliance##i.Reputationalliance lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample results full model.xls", e(all)


/*robustness check with firm age*/


logit treated1 lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample results full model firm age robustness check.xls", e(all)

logit treated1 CVC alliance lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample results full model firm age robustness check.xls", e(all)

logit treated1 c.CVC##c.age c.alliance##c.age lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample results full model firm age robustness check.xls", e(all)

logit treated1 c.CVC##c.age c.alliance##c.age c.CVC##i.CVCreputation c.alliance##i.Reputationalliance lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample results full model firm age robustness check.xls", e(all)


/*robustness check with high reputation cvc investors and alliance partners and firm age*/


logit treated1 cvchighrep cvcother alliancehighrep allianceother age i.startup7years lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample results full model firm age robustness check.xls", e(all)


/*margins at means*/
```

```
logit treated1 lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

margins, dydx(*) atmeans

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample margins results.xls", e(all)

logit treated1 CVC alliance lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

margins, dydx(*) atmeans

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample margins results.xls", e(all)

logit treated1 c.CVC##i.startup7years c.alliance##i.startup7years lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

margins, dydx(*) atmeans

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample margins results.xls", e(all)

logit treated1 c.CVC##i.CVCreputation c.alliance##i.Reputationalliance lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

margins, dydx(*) atmeans

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample margins results.xls", e(all)

logit treated1 c.CVC##i.startup7years c.alliance##i.startup7years c.CVC##i.CVCreputation c.alliance##i.Reputationalliance lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

margins, dydx(*) atmeans

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample margins results.xls", e(all)


/*predictive margins at different values of independent variables and interaction terms*/


logit treated1 c.CVC##i.startup7years c.alliance##i.startup7years lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

margins, at( startup7years=(0 1) CVC=(0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18))

margins, at( startup7years=(0 1) alliance =(0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18))
```

logit treated1 c.CVC##i.CVCreputation c.alliance##i.Reputationalliance lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

margins, at(CVCreputation =(0 1) CVC=(0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18))

margins, at(Reputationalliance =(0 1) alliance =(0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18))

logit treated1 c.CVC##c.age c.alliance##c.age lnliquidity_w lnsize_w roa_w lnpatentcount rand i.dnorand i.dstatus i.twodigitSIC i.year [iweight=cem_weights]

margins, at(CVC=(0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18) age=(0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100))

margins, at(alliance =(0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18) age=(0 5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80 85 90 95 100))

outreg2 using "C:\Users\user\Desktop\PHD DATA\P1 Sample\Study 1 sample predictive margins results.xls", e(all)

/*interaction effects graphs*/

// generate interaction effects graph between CVC and age

gen cvcage = CVC*age

tab cvcage

logit treated1 CVC age cvcage

inteff treated1 CVC age cvcage, savegraph1 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph1"

inteff treated1 CVC age cvcage, savegraph2 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph2"

// generate interaction effects graph between alliance and age

gen allianceage = alliance*age

tab allianceage

logit treated1 alliance age allianceage

inteff treated1 alliance age allianceage, savegraph1 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph1"

```
inteff treated1 alliance age allianceage, savegraph2 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph2"

// generate interaction effects graph between CVC and startup

gen cvcstartup = CVC*startup7years
tab cvcstartup
logit treated1 CVC startup7years cvcstartup
inteff treated1 CVC startup7years cvcstartup, savegraph1 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph1"
inteff treated1 CVC startup7years cvcstartup, savegraph2 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph2"

// generate interaction effects graph between alliance and startup

gen alliancestartup = alliance*startup7years
tab alliancestartup
logit treated1 alliance startup7years alliancestartup
inteff treated1 alliance startup7years alliancestartup, savegraph1 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph1"
inteff treated1 alliance startup7years alliancestartup, savegraph2 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph2"

// generate interaction effects graph between CVC and CVC Partner Reputation

gen cvcrep = CVC*CVCreputation
tab cvcrep
logit treated1 CVC CVCreputation cvcrep
inteff treated1 CVC CVCreputation cvcrep, savegraph1 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph1"
inteff treated1 CVC CVCreputation cvcrep, savegraph2 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph2"

// generate interaction effects graph between alliance and Alliance Partner Reputation
```

```
gen alliancerep = alliance*Reputationalliance

tab alliancerep

logit treated1 alliance Reputationalliance alliancerep

inteff treated1 alliance Reputationalliance alliancerep, savegraph1 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph1"

inteff treated1 alliance Reputationalliance alliancerep, savegraph2 "C:\Users\user\Desktop\PHD DATA\P1 Sample\graph2"

*********************************************************************************

********************** Acquiring Firm Sample ***************************************

use "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\FAME UK Public Acquirers.dta"

label variable newid "Acquiring firm ID"

label variable year "acquisition year"

label variable Companyname "Acquiring firm name"

label variable pairid "Pair ID"

label variable acquirer "Acquiring firm"

label variable year "observation year"

label variable acquisitionyear "year of acquisition"

label variable acquisition "Acquisition"

label variable treat1 "Acquiring firm"

label variable regnumber "Acquiring firm registered number"

label variable bvdid "acquiring firm BVD ID"

label variable country "acquiring firm country"

label variable status "acquiring firm public status"

label variable industrySIC "acquiring firm 4-digit industry SIC Code"

label variable threedigsic "acquiring firm 3-digit industry SIC Code"
```

```
label variable twodigsic "acquiring firm 2-digit SIC Code"
label variable doiyear "acquiring firm date of incorporation year"
label variable size "acquiring firm size"
label variable roa "acquiring firm profitability"
label variable liquidity "acquiring firm liquidity"
label variable rand "acquiring firm R&D Expenditure"

//desc

sum

* log transformation and winsorizing

// generate log transformed variable for acquiring firms' size
gen lnsize = ln(size)

// winsorize log transformed acquiring firms' size
winsor2 lnsize, cut(1 99)

// winsorize acquiring firms' liquidity
winsor2 liquidity, cut(1 99)

// winsorize acquiring firms' profitability
winsor2 roa, cut(1 99)

// Label the new variables

label variable lnsize "acquiring firm size log transformed"
label variable lnsize_w "acquiring firm size winsorized"
label variable roa_w "acquiring firm profitability winsorized"
label variable liquidity_w "acquiring firm liquidity winsorized"
```

```
/*destring variables*/

destring, replace

sum, detail

/*descriptive statistics before CEM*/

sum
sum if treat1==1
sum if treat1==0

imb lnsize_w roa_w industrySIC year, tr(treat1)
cem lnsize_w roa_w industrySIC(#0) year(#0), tr(treat1) showbreaks
tab cem_matched

//Label the new variables

label variable cem_strata "acquiring firms' cem_strata"
label variable cem_matched "acquiring firms' cem_matched variable"
label variable cem_weights "acquiring firms' cem_weights"

/*descriptive statistics after CEM*/

sum
sum if treat1==1
sum if treat1==0

****************************************************************************************
```

********************** Post-Acquisition Innovation Performance Models ***************

* import excel file

import excel "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 2 and 3 sample post acquisition innovation performance analyses.xls", sheet("Sheet1") firstrow

********************** Label variables ***

label variable target_name "target company name"

label variable target_newid "target firm ID"

label variable pairid "Pair ID of acquirer and target firm"

label variable year "acquisition year"

label variable postacqtime "post acquisition time period"

label variable target_count "target count variable"

label variable target_patents "patents of target firms"

label variable target_cits "citations received by target firm patents"

label variable target_reg_number "target firm registered number"

label variable target_bvdid "target firm BVD ID"

label variable target_country "target firm country"

label variable target_industrySIC "target firm 4-digit industry SIC Code"

label variable target_threedigitSIC "target firm 3-digit industry SIC Code"

label variable target_twodigitSIC "target firm 2-digit industry SIC Code"

label variable target_status "target firm private status"

label variable target_dstatus "target firm private status dummy variable"

label variable target_lnliquidity_w "target firm liquidity"

label variable target_lnsize_w "target firm size"

label variable target_roa_w "target firm profitability"

label variable target_CVC "target firm CVC investments"

label variable target_alliance "target firm alliances"

label variable target_rand "target firm R&D Expenditure" label variable target_dnorand "target firm dummy variable for missing values of R&D expenditure"

label variable target_age "target firm age"

label variable target_startup "target firm start up"

label variable target_doiyear "target firm date of incorporation year"

label variable tartget_cem_strata "target firm cem_strata"

label variable target_cem_matched "target firm cem_matched variable"

label variable target_cem_weights "target firm weights from cem"

label variable centercvc "cvc centered at mean"

label variable centeralliance "alliance centered at mean"

label variable related "acquirer and target with same 4-digit industry SIC Codes"

label variable acquirer_name "acquirer company name"

label variable merged "merged pair of acquirer and target firms"

label variable acquirer_patents "patents of acquiring firms"

label variable combined_patents "patents of combined acquired and acquiring firms"

label variable acquirer_cits "citations received by acquiring firm patents"

label variable combined_cits "acquired and acquiring firm combined citations received per patents"

label variable acquirer_newid "acquiring firm ID"

label variable acquirer_reg_number "acquiring firm registered number"

label variable acquirer_bvdid "acquiring firm BVD ID"

label variable acquirer_country "acquiring firm country"

label variable acquirer_status "acquiring firm public status"

label variable acquirer_industrySIC "acquiring firm 4-digit industry SIC Code"

label variable acquirer_threedigSIC "acquiring firm 3-digit industry SIC Code"

label variable acquirer_twodigSIC "acquiring firm 2-digit industry SIC Code"

label variable acquirer_doiyear "acquiring firm date of incorporation year"

label variable acquirer_lnsize_w "acquiring firm size"

label variable acquirer_roa_w "acquiring firm profitability"

label variable acquirer_liquidity_w "acquiring firm liquidity"

label variable acquirer_rand "acquiring firm R&D expenditure"

label variable acquirer_cem_strata "acquiring firm cem_strata"

```
label variable acquirer_cem_matched "acquiring firm cem_matched variable"
label variable acquirer_cem_weights "acquiring firm weights from cem"

/* descriptive statistics of Study 2: Acquired Firm Innovation Performance Model*/

sum
sum if target_count==1
sum if target_count==0
pwcorr target_count postacqtime target_CVC target_alliance target_lnsize_w target_roa_w target_lnliquidity_w target_rand target_dnorand target_dstatus target_patents target_cits, star(0.05)

//generate centered variables

sum target_CVC target_alliance
gen centercvc = target_CVC - r(mean)
gen centeralliance = target_alliance - r(mean)

/*Study 2: triple differences and difference-in-differences analyses with patent
output as dependent variable*/

poisson target_patents i.target_count##i.postacqtime target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.target_dnorand i.target_dstatus i.target_twodigitSIC i.year [iweight=target_cem_weights]
outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 2 results using patent and citations data.xls", e(all)
poisson target_patents i.target_count##i.postacqtime##c.centercvc target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.target_dnorand i.target_dstatus i.target_twodigitSIC i.year [iweight=target_cem_weights]
outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 2 results using patent and citations data.xls", e(all)
poisson target_patents i.target_count##i.postacqtime##c.centeralliance target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.target_dnorand i.target_dstatus i.target_twodigitSIC i.year [iweight=target_cem_weights]
```

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 2 results using patent and citations data.xls", e(all)

poisson target_patents i.target_count##i.postacqtime##c.centercvc i.target_count##i.postacqtime##c.centeralliance target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.target_dnorand i.target_dstatus i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 2 results using patent and citations data.xls", e(all)

/*Study 2: triple differences and difference-in-differences analyses with citation

output as dependent variable*/

poisson target_cits i.target_count##i.postacqtime target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.target_dnorand i.target_dstatus i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 2 results using patent and citations data.xls", e(all)

poisson target_cits i.target_count##i.postacqtime##c.centercvc target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.target_dnorand i.target_dstatus i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 2 results using patent and citations data.xls", e(all)

poisson target_cits i.target_count##i.postacqtime##c.centeralliance target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.target_dnorand i.target_dstatus i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 2 results using patent and citations data.xls", e(all)

poisson target_cits i.target_count##i.postacqtime##c.centercvc i.target_count##i.postacqtime##c.centeralliance target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.target_dnorand i.target_dstatus i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 2 results using patent and citations data.xls", e(all)

/*Study 3: Post-Acquisition Innovation Performance of Merged (Acquired and Acquiring)

Firms*/

// generate combined patents of acquired and acquiring firms

```
gen combined_patents = (target_patents) + (acquirer_patents)

// generate combined citations of acquired and acquiring firms

gen combined_cits = (target_cits) + (acquirer_cits)

/*descriptive statistics of study 3 on merged pairs post-acquisition innovation
performance*/

sum
sum if merged==1
sum if merged==0
pwcorr merged postacqtime combined_patents combined_cits target_CVC target_alliance acquirer_lnsize_w acquirer_roa_w acquirer_liquidity_w acquirer_rand related, star(0.05)

/* Study 3: triple differences and difference-in-differences analyses with patent
output as dependent variable*/

poisson combined_patents i.merged##i.postacqtime acquirer_liquidity_w acquirer_lnsize_w acquirer_roa_w acquirer_rand i.related i.acquirer_twodigSIC i.year [iweight=acquirer_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results using patent and citations data.xls", e(all)

poisson combined_patents i.merged##i.postacqtime##c.centercvc acquirer_liquidity_w acquirer_lnsize_w acquirer_roa_w acquirer_rand i.related i.acquirer_twodigSIC i.year [iweight=acquirer_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results using patent and citations data.xls", e(all)

poisson combined_patents i.merged##i.postacqtime##c.centeralliance acquirer_liquidity_w acquirer_lnsize_w acquirer_roa_w acquirer_rand i.related i.acquirer_twodigSIC i.year [iweight=acquirer_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results using patent and citations data.xls", e(all)
```

poisson combined_patents i.merged##i.postacqtime##c.centercvc i.merged##i.postacqtime##c.centeralliance acquirer_liquidity_w acquirer_lnsize_w acquirer_roa_w acquirer_rand i.related i.acquirer_twodigSIC i.year [iweight=acquirer_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results using patent and citations data.xls", e(all)

/* Study 3: triple differences and difference-in-differences analyses with citation

output as dependent variable*/

poisson combined_cits i.merged##i.postacqtime acquirer_liquidity_w acquirer_lnsize_w acquirer_roa_w acquirer_rand i.related i.acquirer_twodigSIC i.year [iweight=acquirer_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results using patent and citations data.xls", e(all)

poisson combined_cits i.merged##i.postacqtime##c.centercvc acquirer_liquidity_w acquirer_lnsize_w acquirer_roa_w acquirer_rand i.related i.acquirer_twodigSIC i.year [iweight=acquirer_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results using patent and citations data.xls", e(all)

poisson combined_cits i.merged##i.postacqtime##c.centeralliance acquirer_liquidity_w acquirer_lnsize_w acquirer_roa_w acquirer_rand i.related i.acquirer_twodigSIC i.year [iweight=acquirer_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results using patent and citations data.xls", e(all)

poisson combined_cits i.merged##i.postacqtime##c.centercvc i.merged##i.postacqtime##c.centeralliance acquirer_liquidity_w acquirer_lnsize_w acquirer_roa_w acquirer_rand i.related i.acquirer_twodigSIC i.year [iweight=acquirer_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results using patent and citations data.xls", e(all)

/*Study 3: DDD and DID analyses on targets that are merged with acquiring firms using

patent output as dependent variable*/

poisson target_patents i.targetcount##i.postacqtime target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.drand i.target_dstatus i.related i.target_twodigitSIC i.year [iweight=target_cem_weights]

```
outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results on targets using patent and citations data.xls", e(all)

poisson target_patents i.targetcount##i.postacqtime##c.centercvc target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.drand i.target_dstatus i.related i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results on targets using patent and citations data.xls", e(all)

poisson target_patents i.targetcount##i.postacqtime##c.centeralliance target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.drand i.target_dstatus i.related i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results on targets using patent and citations data.xls", e(all)

poisson target_patents i.targetcount##i.postacqtime##c.centercvc i.targetcount##i.postacqtime##c.centeralliance target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.drand i.target_dstatus i.related i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results on targets using patent and citations data.xls", e(all)


/*Study 3: DDD and DID analyses on targets that are merged with acquiring firms using

citation output as dependent variable*/


poisson target_cits i.targetcount##i.postacqtime target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.drand i.target_dstatus i.related i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results on targets using patent and citations data.xls", e(all)

poisson target_cits i.targetcount##i.postacqtime##c.centercvc target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.drand i.target_dstatus i.related i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results on targets using patent and citations data.xls", e(all)

poisson target_cits i.targetcount##i.postacqtime##c.centeralliance target_lnliquidity_w target_lnsize_w target_roa_w target_rand i.drand i.target_dstatus i.related i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results on targets using patent and citations data.xls", e(all)

poisson target_cits i.targetcount##i.postacqtime##c.centercvc i.targetcount##i.postacqtime##c.centeralliance target_lnliquidity_w target_lnsize_w
```

target_roa_w target_rand i.drand i.target_dstatus i.related i.target_twodigitSIC i.year [iweight=target_cem_weights]

outreg2 using "C:\Users\user\Desktop\PHD DATA\P3 DATA\Study 2 and 3 samples and analyses\Study 3 results on targets using patent and citations data.xls", e(all)

APPENDIX D

Non-linear test was conducted to check the size of the coefficients of the variables CVC investments and alliances.

β_1 indicates a positive and statistically significant coefficient of CVC investments (0.084, p<0.01), which can be converted to percentage points as follows: 0.0840 X 100 = 8.4 percentage points. β_2 indicates a positive and statistically significant coefficient of alliances (0.027, p<0.01), which can be converted to percentage points [0.027 X 100 = 2.7 percentage points].

The coefficient on CVC investments indicates a higher probability of acquisition likelihood (8.4 percentage points) as compared to alliances whose coefficient on the probability of acquisition likelihood is lower (2.7 percentage points).

```
. nl (treated1 = {b0} + {b1}*CVC + {b2}*alliance), variables(CVC alliance)
(obs = 3,798)

Iteration 0:  residual SS =   399.693
Iteration 1:  residual SS =   399.693
```

Source	SS	df	MS
Model	17.399407	2	8.69970335
Residual	399.69301	3795	.105320951
Total	417.09242	3797	.109847884

Number of obs	=	3,798
R-squared	=	0.0417
Adj R-squared	=	0.0412
Root MSE	=	.3245319
Res. dev.	=	2226.934

treated1	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b0	.1131906	.0053695	21.08	0.000	.1026634	.1237179
/b1	.0840867	.0077778	10.81	0.000	.0688375	.0993358
/b2	.0272412	.0039389	6.92	0.000	.0195187	.0349637

Parameter b0 taken as constant term in model & ANOVA table